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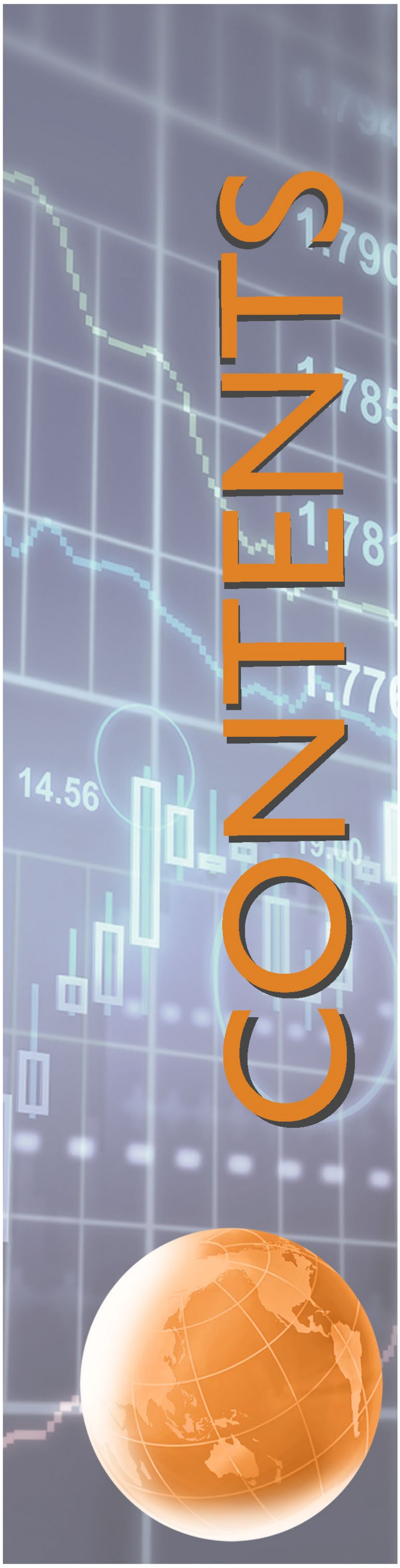

IMPACTS OF RISK PREFERENCE AND SOCIAL INSURANCE ON HOUSEHOLD FINANCIAL MARKET PARTICIPATION IN CHINA: ARE THERE DIFFERENCES BETWEEN URBAN AND RURAL RESIDENTS?

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Abstract

This letter examines the impact of risk preference and social insurance on household financial market participation and diversification using the 2017 and 2019 China Household Finance Survey. A multi-value treatment model addresses the selection bias between risk preference and household financial investment, considering the moderation role of social insurance in between. Overall, our results show that high-risk takers are more likely to participate in the financial market and diversify their portfolios than low-risk takers. Focusing on rural and urban differentials, we find marked differences in the impacts of risk preference and social insurance on household financial investment. Having social insurance may widen the difference in investment decisions between high- and low-risk takers in urban areas; the latter group tends not to participate in or diversify when socially insured. In contrast, having social insurance encourages low- and intermediate-risk preferred rural households to participate in the financial market and diversify their financial portfolios. Our work highlights the different consequences of social insurance on investment incentives for rural and urban households. Whilst there are obvious benefits of having social insurance for rural households via risk-sharing, there is an undesired consequence of incentive distortion of urban households.

Keywords: risk preference, financial market participation, diversification, social insurance, multi-value treatment model, rural and urban households

1. Introduction

One basic question raised in household finance research is how households allocate their assets among categories such as bonds, shares, and funds (Campbell, 2006). Many people do not hold stocks (Badarinza et al., 2016; Haliassos and Bertaut, 1995; Mankiw and Zeldes, 1991): there is 24% direct equity market participation in the U.S. and the U.K., 22% in Canada, 27% in the Netherlands and Germany, and 38% in Australia. A body of literature has explored the effect of household preference, risk-based factors, the cost of participation, and peer effects on stock market participation (Gomes et al., 2021). An important household asset class that has received less attention is insurance products. Social insurance as a tool for risk mitigation is commonly known as government-sponsored programs providing benefits and services in response to contingencies such as ageing, sickness, unemployment, maternity, and work injury. Its implementation and consequent impact vary across countries, influenced by factors like historical development (Esping-Andersen, 1990), economic structure (Barr, 2001), and socio-political contexts (Pierson, 1996).

The accessibility and coverage of social insurance may affect household financial behaviours. Social insurance affects income redistribution because benefits are paid to those who suffered negatively due to the event that triggered the payment of benefits (Chen et al., 2022). With this additional risk-free asset class, we shall see households having social insurance would increase their risk-taking. However, the risk protection benefits come at a cost known as the moral hazard. Moral hazard has been shown to distort the incentives of households, leading to early retirement, low savings, and excessive medical care consumption (Feldstein, 2005). From this perspective, socially insured households may reduce risk-taking.

China, as the largest emerging economy, offers a good context for this study, due to its evolving nature and urban-rural disparity in accessibility to social insurance. The inception of China's contemporary social insurance scheme can be traced back to the 1990s. This period witnessed the gradual evolution of what is now commonly referred to as the "Five Insurances Scheme", including pension insurance, medical insurance, unemployment insurance, work-related injury insurance, and maternity insurance (Gao et al., 2019). Note that these components were introduced at varying points, mainly in the late 1990s. The focus was predominantly on urban residents and those who worked in state-owned enterprises as they occurred in conjunction with urban and state-owned enterprise economic reforms (i.e., pension from government and public institutions). Thus, it only covers 23% of the urban population by 2000 (Gao et al., 2019). Then, the cohesive system began to form in good shape in the early 2000s under the framework targeting all urban residents, namely basic pension insurance for urban employees and social insurance for urban residents. After 2004, the primary objective shifted towards expanding coverage to include rural residents and employees in the private sector (Gao et al., 2019). This expansion was implemented under principles emphasizing socialization, basic coverage, and broad inclusivity (i.e., the new social insurance for rural residents). The coverage of social insurance in rural areas has a significant expansion in the last 15 years: the government has heavily subsidized the rural residents toward contributions, hoping to establish a unified system for urban and rural residents (Gao et al., 2019; Lei et al., 2013; Rickne, 2013). By 2016, basic pension insurance and basic medical insurance extended to nearly 90% of China's population (Gao et al., 2019). Hence, till now, most rural residents are covered by basic pension insurance and basic medical insurance, compared to their urban peers most of whom have access to all “Five” social insurance categories.

Given China’s evolving social insurance development and its urban-rural disparities, a question arises: how do those dynamics influence household financial behaviours? It is unclear whether the effects of risk-based factors on financial market participation differ between urban and rural households and how social insurance could moderate the differences.

This letter is the first attempt to empirically examine how social insurance alters the risk preference on household investment decisions, focusing on rural and urban differentials. We tackle three related issues using the 2017 and 2019 China Household Finance Survey. We first correct the self-selection bias using a multi-valued treatment effect model to estimate financial market participation and diversification. Risk-averse individuals, who are less likely to search for relevant investment information, may choose to participate less than high-risk takers and be incorrectly deemed as undiversified when it is only the risk preference that differs (Weber and Milliman, 1997). An individual’s risk preference does not change in the short term, but it may change with one’s financial risk tolerance which can be improved by one’s achievement in financial success or increased certainty of one’s financial situation (Grable, 2000; Van de Venter et al., 2012). Hence, we further explore how social insurance changes household financial participation and diversification decisions depending on the risk preferences they hold. Last, we conduct a heterogeneity examination to deal with rural and urban differences in financial participation and diversification.

2. Data

Data were sourced from the 2017 and 2019 China Household Finance Survey (CHSF)[1]. The CHFS is a nationwide household survey covering 1360 communities and villages in 29 provinces in China; 9,214 households were excluded because of incomplete information, producing a final sample of 36,153 households.

The outcome variables ($Y_{1,2}$) are financial investment decisions[2]. Y_1 represents households' finance participation, equalling one if a household invested in any risky financial assets such as stocks, bonds, funds, derivatives, financial products, gold, and non-RMB assets, and zero otherwise. Y_2 measures households' financial diversification, taking the value n if the household invested in n risky financial assets.

The treatment is the risk attitude of the household head, based on the survey question: if you have a fund for investment, which investment project would you most like to choose? Respondents are considered high-risk takers when they choose high-risk and high-return projects or projects with slightly high-risk and slightly high-return. Respondents are intermediate-risk takers if they choose projects with average risk and returns. Those selecting the option 'not willing to take any risks' were the low-risk preference group. Tables 1 and 2 provide variable definitions and descriptive statistics. In our sample, 48.2% of respondents invested in one or more risky financial asset classes. Nearly three-quarters of households (74.7%) were in the low-risk preference group, followed by 17.5% in the intermediate-risk preference group, and only 7.7% were in the high-risk group. The average total household income and assets were 78,370 RMB (11,342 USD) and 830,552 RMB (120,196 USD), respectively; 79.5% of household heads had social insurance.

Table 1: Variable Definitions

Variable	Description
Participation	Is a dummy variable to show the financial participation of households. The variable equals 1 if a household has any investment in stocks, funds, financial products, bonds, derivatives, gold (excluding jewellery), and non-RMB assets, other financial assets, or lend-out money, and zero otherwise.
Diversification	This measures the diversification of household financial investments. If households have n financial asset classes, then the value is n. There are the following financial asset classes: stocks, funds, financial products, bonds, derivatives, gold (excluding jewellery), and non-RMB assets, other financial assets, and lend-out money. If households do not participate in any financial investment, then the variable value is zero.
Treatment	Households are divided into three categories according to their risk attitude. A value of 1 represents high-risk preference, 2 represents intermediate-risk preference, and 3 represents low-risk preference.
Total_income	Amount of annual household income. It consists of income from wages and salary, net profit from agricultural and business activities, income from all forms of property, and transfer income.
Total asset	Amount of total household assets. It consists of financial assets and non-financial assets (e.g., a house).
Rural	This is a dummy variable equal to 1 when the household is in a rural area and zero otherwise.
Age	Age of the head of the household in years.
Gender	The gender of the head of the household is equal to 1 if male and zero otherwise.

[1] We have noticed that there are 5 available waves of the survey. However, the key variables, i.e., risk preference, financial participation and diversification, and social insurance are only consistently available in the two waves chosen in the study (2017 and 2019 surveys). Hence, we are not allowed to include more waves due to data availability.

[2] House ownership and social pension insurance participation were not included as financial investments for both participation and diversification measures.

Education	Education level of the head of household. It is a categorical variable: no schooling at all (=1), primary school (=2), junior high (=3), high school (=4), technical secondary school (=5), junior college (=6), bachelor's degree (=7), master's degree (=8), doctorate (=9).
Married	Marital status, which equals 1 if married and zero otherwise.
Social insurance	This is a dummy variable equal to 1 if the household has any of the following social insurances: pension from a government or public institution; basic pension insurance for urban employees; new social insurance for rural residents; social insurance for urban residents; social insurance for urban and rural residents, and zero otherwise. Note that the above social insurance systems may differ due to the different types of insurance included in each system. For example, for most urban insurers, their social insurances cover the "Five Insurances Scheme", including pension insurance, medical insurance, unemployment insurance, work-related injury insurance, and maternity insurance, whilst their rural peers under the framework of "new rural social insurance for rural residents" only get the basic coverage of pension and medical insurance.
Hukou (household registration)	A household registration record that officially identifies a person as a resident of an area. It is a categorical variable with four types: agricultural, non-agricultural, unified hukou, and other. The number of observations in the category "others" is 26, which are excluded from the sample. Three types of hukou are included in this study.
Health	Compared with peers, the condition of the head of household: very good (=1), good (=2), ordinary (=3), bad (=4), and very bad (=5).
Year	This is a dummy variable equal to 1 if the observation is from the 2019 survey and equal to 0 if the observation is from 2017.

Table 2: Descriptive Statistics of the Variables

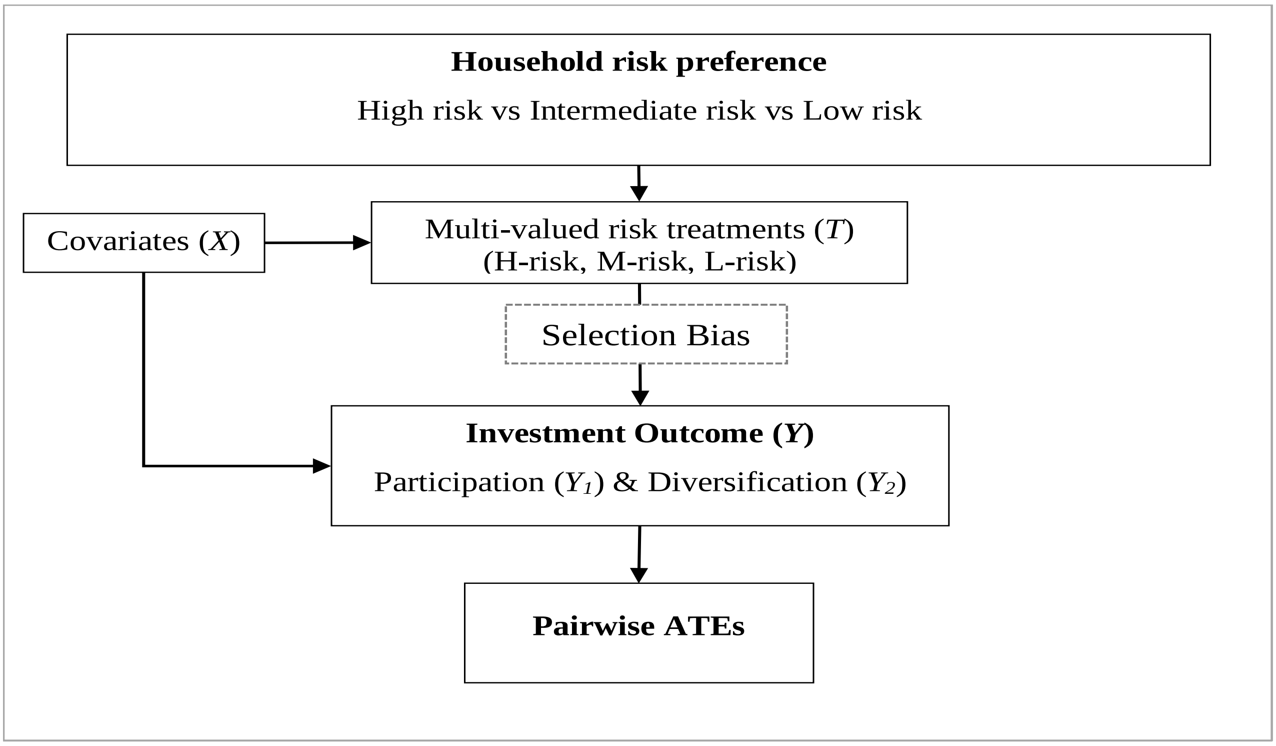
Variable	Mean	Std. Dev.	Minimum	Maximum	Observations
Outcome Y					
Participation	0.482	0.500	0.000	1.000	36,153
Diversification	1.390	0.840	1.000	7.000	19,297
Treatment T					36,153
H-risk treatment	0.077	0.267	0.000	1.000	2,820
M-risk treatment	0.175	0.380	0.000	1.000	6,327
L-risk treatment	0.747	0.435	0.000	1.000	27,007
Covariate X					
total income (1,000 RMB)	78.370	90.786	-990.965	999454.000	36,153
total asset (1,000 RMB)	830.552	1005.143	1.000	4999.110	36,153
rural	0.299	0.458	0.000	1.000	36,153
age	56.690	15.015	21.000	99.000	36,153
gender	0.519	0.500	0.000	1.000	36,153
education	3.566	1.712	1.000	9.000	36,153
married	0.929	0.257	0.000	1.000	36,153
social insurance	0.795	0.404	0.000	1.000	36,153
hukou:					36,153
1. agriculture	0.513	0.500	0.000	1.000	18,559
2. non-agriculture	0.339	0.473	0.000	1.000	12,268
3. unified	0.147	0.354	0.000	1.000	5,326
health	2.640	0.991	1.000	5.000	36,153
year	0.632	0.686	0.000	1.000	36153

3. Methods

3.1 Conceptual Analysis Framework

Individuals' preferences affect investing decisions like stock ownership (Ert and Haruvy (2017)). Note that risk preference is not merely an exogenous trait that individuals are born with; rather, it evolves based on several factors including cognitive ability (Dohmen et al., 2010), household endowment (Guiso & Paiella, 2008), and past macroeconomic experiences (Malmendier & Nagel, 2011). This dynamic nature of risk preference makes it endogenous to the investment decision-making process. Individuals with a low-risk preference might avoid the stock market altogether, not because of the inherent risks of the market, but due to their negative past macroeconomic experiences (Malmendier & Nagel, 2011). This self-selection can bias the observed relationship between risk preference and investment. Hence, different from previous studies (e.g., Yang et al. (2019)) that included it as an exogenous variable, this study addressed the self-selection bias by a multi-valued treatment effects model shown in Figure 1.

Figure 1: Conceptual analysis framework of the study



Here, households were grouped by their risk preference for financial assets: high-risk (H-risk), intermediate-risk (M-risk), and low-risk (L-risk). For i^{th} household $(i = 1, 2, \ldots, n)$, there is an observed vector $F_i = (T_i, X_i, Y_i)'$, where T_i is the treatment status; $Y_i = (Y_{1i}, Y_{2i})$ represents the outcome variables, with Y_{1i} denoting whether, or not, to participate in the financial market and Y_{2i} denoting the number of financial assets invested; and X_i is the vector of observed covariates (e.g., characteristics of household heads) to be used in the treatment-outcome process (Cuong, 2013). Details of differences across risk groups are included in the online Appendix.

3.2 Empirical Specifications

We use a "doubly robust" approach (IPTW) to estimate the pairwise average treatment effect (ATEs) through a weighted linear regression model with the weighting drawn from the multi-valued treatment process (Boonstra et al., 2014; McCaffrey et al., 2013). The ATEs of risk preference on participation are estimated through:

$$\log\left(\frac{\text{Prob}(Y_{1i}=1)}{\text{Prob}(Y_{1i}=0)}\right) = \alpha_i + \delta_1 T_2 + \delta_2 T_3 + X_i\beta + \varepsilon_i, \tag{1}$$

where δ_1 and δ_2 represent the IPTW estimator used to estimate the ATE between the M- and H-risk group and between the L- and H-risk group, respectively; the H-risk group is the baseline. For the diversification model, we assume the number of financial assets, y_i, is drawn from a Poisson population with the parameter λ_i:

$$Prob(\,Y_2 = y_i|X_i) = \frac{exp(-\lambda_i)\lambda_i^{y_i}}{y_i!}, y_i = 0,1,2,\ldots m. \tag{2}$$

The Poisson regression model estimates the ATEs of risk preference on diversification:

$$ln\,\varpi_i = \alpha_i + \gamma_1 T_2 + \gamma_2 T_3 + X_i\mu + \varepsilon_i, \tag{3}$$

where γ_1 and γ_2 represent the ATE between the M- and H-risk group and between the L- and H-risk group, respectively.

As stated in the conceptual framework, we tend to explore if social insurance could moderate the risk preference effect on household investment decisions. Hence, we add a variable, social insurance, and its interactions with risk treatments T_2 and T_3 to Equation (1) and Equation (3) to test for the moderation role of social insurance on risk preference effect on financial participation and diversification.

4. Results and Discussion

4.1 Results of the risk preference and social insurance on investment participation and diversification

Table 3 reports regression results from Equations (1) and (3). Low-risk households are 0.571 times less likely to invest than high-risk households. This is consistent with studies by Guiso et al. (2008) and Yang et al. (2019). We found no significant differences between High- and intermediate-risk households in the participation tendency. Similar to financial market participation, risk preference affects diversification. Low-risk takers are 0.732 times less likely to diversify a portfolio than high-risk takers, but the effect is not significant between the high- and intermediate-risk groups. These results indicate that household investment decisions on financial assets differ only between the two extremely different risk preference groups. The high-risk group intends to invest and invest in multiple asset classes to diversify risk. In contrast, the low-risk group prefers low-risk assets, therefore they are less likely to invest in high-risk assets and don't need to diversify.

Table 3: The Effects of Risk Preferences on Financial Market Participation and Diversification

Variable	Model			
	Participation		Diversification	
	Odds Ratio	standard error	IRRs	standard error
(1)	(2)	(3)	(4)	(5)
ATE ($\hat{\delta}_1$)	1.011	-0.028		
ATE ($\hat{\delta}_2$)	0.571***	-0.016		
ATE ($\hat{\gamma}_1$)			0.989	-0.063
ATE ($\hat{\gamma}_2$)			0.732***	-0.027
total income	1.000***	0.000002	1.000***	0.000001
total asset	1.000***	0.000002	1.000***	0.000001
rural	0.541***	-0.011	0.754***	-0.082
age	0.961***	-0.001	0.977***	-0.002
gender	0.993	-0.024	0.976	-0.083
education	1.180***	-0.007	1.092***	-0.010
married	1.967***	-0.004	1.334***	-0.065
hukou (non-agriculture)	1.100***	-0.025	1.240**	-0.091
hukou (unified)	1.152	-0.096	1.198	-0.093
health	0.844***	-0.008	0.901***	-0.028
year	4.665***	0.018	1.896***	0.052
constant	5.381***	-0.073	1.011	-0.238
Observations	36,153		36,153	
Log Likelihood	-34,319.46		-263,357.51	
Akaike Inf. Crit.	3,195.65		462,481.76	

Note: For ease of interpretation, we exponentiated the coefficient estimates of the participation (binary logit regression) and diversification model (Poisson count regression) to derive odds ratio and incidence rate ratio (IRR); *p<0.1; **p<0.05; ***p<0.01.

We further explore how social insurance changes the investment incentives of insured households and present the results in Table 4. We found that having social insurance may lead high-risk households to be 1.103 times more likely to invest than those not having one. The interaction effect affects low-risk households undesirably. Low-risk households with social insurance are less likely to invest (diversify) than high-risk households with a factor of 0.941 (0.785). The results indicate that having social insurance may encourage high-risk households to invest (Yang et al., 2019) but discourage low-risk households from investing or diversifying as they feel adequate financial security is provided by social insurance (Feldstein, 2005).

Table 4: Social insurance Effect on the relationship between Risk preference and Financial Market participation and Diversification

Variable	Model 2			
	Participation		Diversification	
	Odds Ratio	standard error	IRRs	standard error
(1)	(2)	(3)	(4)	(5)
ATE ($\hat{\delta}_1$)	0.991	-0.032		
ATE ($\hat{\delta}_2$)	0.789***	-0.021		
ATE ($\hat{\gamma}_1$)			0.951	-0.146
ATE ($\hat{\gamma}_2$)			0.841**	-0.084
Social insurance	1.103***	-0.019	1.242	-0.106
$\hat{\delta}_1$*Social insurance	1.098	-0.062		
$\hat{\delta}_2$* Social insurance	0.941**	-0.015		
$\hat{\gamma}_1$*Social insurance			1.107	-0.218
$\hat{\gamma}_2$* Social insurance			0.785**	-0.097
Control variables	Yes		Yes	
Observations	36,153		36,153	
Log Likelihood	-42,483.89		-186,472.03	
Akaike Inf. Crit.	68,933.00		429,307.04	

Note: Control variables are the same as in Table 1. For ease of interpretation, we exponentiated the coefficient estimates of the participation (binary logit regression) and diversification model (Poisson count regression) to derive odds ratio and incidence rate ratio (IRR); *p<0.1; **p<0.05; ***p<0.01.

4.2 Heterogeneity examination: rural versus urban households

We observed marked differences in the effect of risk preference and social insurance on financial market participation and diversification of rural (shown in Model (rural)) and urban households (shown in Model (urban)). As shown in Table 5 (columns 2 and 4), low- and intermediate-risk takers are less likely to invest (diversify) than high-risk takers living in rural areas when there is no social insurance in place; Having social insurance moderated their risk preferences: it helps reduce the differences in both participation and diversification between low- and high-risk preferred households and intermediate- and high- risk preferred households, according to the results of interaction effects. It shows that social insurance has a significant impact on ensuring financial security and motivating rural households to invest and diversify their financial portfolios. Social insurance provides benefits to rural households via risk-sharing, thus encouraging their participation in the financial market and diversification of investment (Meng et al., 2015). For urban households, the results in Table 5 (columns 6 and 8) show that risk preferences only affect low- and high-risk preferred groups when households are not socially insured: low-risk preferred households are less likely to invest and diversify than the high-risk group. We find having social insurance may discourage low- and intermediate-risk preferred households from participating in and diversifying, based on the interactions between risk treatment and social insurance.

The results of previous social insurance studies show that the advantages of social insurance policies vary among targeted groups based on, for example, income and demographic variables. The findings of the rural-urban differences in our study are consistent with the findings of Chen et al.

(2022). We further show social insurance could also have unfavourable effects on incentives for insured low-risk urban takers, lowering their incentives to invest.

Table 5. The Effects of Risk Preferences and Social Insurance on Financial Market Participation and Diversification for the Rural and Urban Sample

Variable	Model (Rural)				Model (Urban)			
	Participation		Diversification		Participation		Diversification	
	Odds Ratio	Standard error	IRRs	Standard error	Odds Ratio	Standard error	IRRs	Standard error
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATE ($\hat{\delta}_1$)	0.896***	0.042			0.978	0.029		
ATE ($\hat{\delta}_2$)	0.839***	0.042			0.773***	0.028		
ATE ($\hat{\gamma}_1$)			0.855***	0.043			0.003	0.023
ATE ($\hat{\gamma}_2$)			0.815***	0.043			0.802***	0.024
Social insurance	0.996	0.034	1.006	0.034	1.181***	0.024	1.202***	0.018
$\hat{\delta}_1$*Social insurance	1.098***	0.048			0.918***	0.033		
$\hat{\delta}_2$* Social insurance	1.099***	0.048			0.840***	0.039		
$\hat{\gamma}_1$*Social insurance			1.067	0.049			0.986***	0.026
$\hat{\gamma}_2$* Social insurance			1.189***	0.049			0.849***	0.030
Control variables	Yes		Yes		Yes		Yes	
Observations	10809				25344			
Log Likelihood		-7788.35		-24003.69		-36693.11		-77800.41
Akaike Inf. Crit.		30708		48041		73420		155635

Note: Control variables are the same as in Table 1. For ease of interpretation, we exponentiated the coefficient estimates of the participation (binary logit regression) and diversification model (Poisson count regression) to derive odds ratio and incidence rate ratio (IRR); *p<0.1; **p<0.05; ***p<0.01.

5. Conclusion

This is the first study to investigate the endogenous effect of household risk preference on financial market participation and diversification. We found that high-risk families are more likely to participate in and diversify investments. When a risk-free asset (social insurance) is introduced to a household's portfolio, it has a positive effect on high-risk households but distorts incentives to low-risk households in the urban area, leading to non-participation and under-diversification. In contrast, having social insurance may provide financial security and encourage low-risk takers to participate in the financial market and diversify investment for rural households. Our finding of the incentive role of social insurance on finance investment of rural households highlights the benefits of social insurance policy in the rural area, whilst the unintended consequence of social insurance also calls for more financial literacy education for the general public.

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Appendix

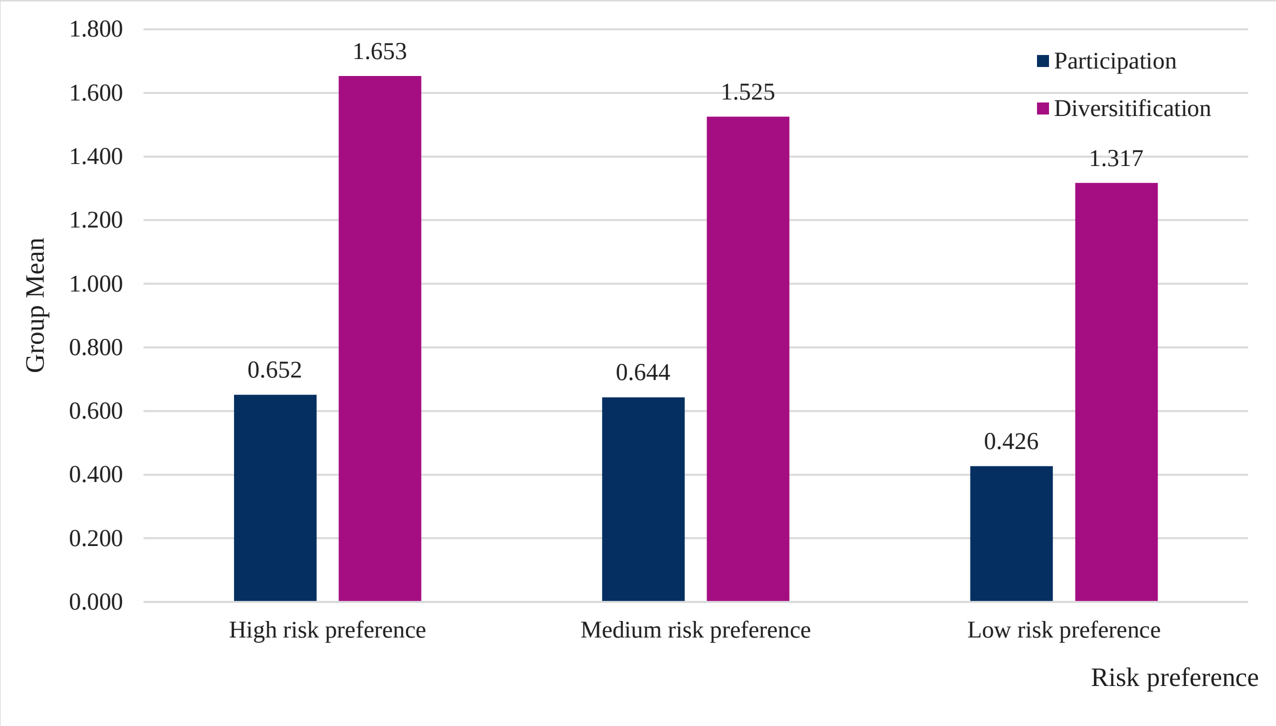
Appendix Table 1: Univariate Analysis by Risk Treatment Groups

Variable	Mean			Mean difference		
	H-risk group	M-risk group	L-risk group	H vs. M	H vs. L	M vs. L
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome Y						
Participation	0.652	0.644	0.426	0.008	0.225***	0.217***
Diversification	1.653	1.525	1.317	0.128	0.208***	0.336***
Covariate X						
total income (1,000 RMB)	105.740	101.978	69.996	3.762	35.744***	31.982***
total asset (1,000 RMB)	1095.784	1039.543	754.045	56.241**	341.739***	285.498***
rural	0.211	0.213	0.328	-0.002	-0.117***	-0.115***
age	48.060	48.25	59.63	-0.19**	-11.57***	-11.38***
gender	0.628	0.508	0.510	0.1204***	0.118***	-0.003
education	4.478	4.346	3.289	0.132***	1.189***	1.057***
married	0.809	0.846	0.961	-0.037***	-0.151***	-0.114***
social insurance	0.728	0.750	0.813	-0.023	-0.085***	-0.062***
hukou:						
1.agriculture	0.439	0.461	0.533	-0.022*	-0.094***	-0.072***
2.non-agriculture	0.392	0.383	0.323	0.008	0.068***	0.060***
3.unified	0.170	0.157	0.143	0.013	0.027***	0.0136***
health	2.402	2.399	2.722	0.003	-0.32***	-0.323***

Note: ***p < 0.01; **p < 0.05; *p < 0.1 for Welch two sample t-test of mean differences in two treatment groups.

We used a t-test (for continuous variables) and a chi-square test (for dummies) to test the significance of the mean differences between the three treatment groups (see Appendix Table 3). The results show that differences in the means of most variables are significant between pairwise groups. For the outcome variables, households in high-risk group have the highest proportion of market participation and invest in more types of financial assets, followed by the intermediate-risk group and the low-risk group. Differences in the means of the outcome variables are significant between the high-risk and low-risk group and between the intermediate-risk and low-risk group. No significant mean difference is observed between the high-risk and intermediate-risk group. Regardless of participation or diversification, the mean difference is larger between the high-risk and low-risk groups than between high-risk and intermediate-risk groups (see Appendix Figure 1).

Appendix Figures 1: A Comparison of Group Means of Participation and Diversification across Risk Treatment Groups



As shown in the above figure, for the outcome variables, households in the high-risk group have the highest proportion of market participation and invest in more types of financial assets, followed by the intermediate-risk group and the low-risk group. That is, regardless of participation or diversification, the mean difference is larger between the high-risk and low-risk groups than between high-risk and intermediate-risk groups.

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INVESTIGATION OF ASYMMETRIC DYNAMICS OF BORSA ISTANBUL INDEX WITH QUANTILE UNIT ROOT TEST

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Abstract

The main contribution of the study is the empirical examination of the Borsa Istanbul Index using Koenker and Xiao's (2004) quantile unit root test, which provides robust inferences for non-normal processes based on the quantile autoregression approach. The study contributes to the portfolio formation based on quantile regression for future studies and highlights the importance of understanding asymmetric inferences in shock magnitude and sign for asset pricing and forecasting in the securities market. The findings indicate that the dynamic structure of the index displays asymmetrical behaviour, introducing quantile perspectives to index dynamics in contrast to conventional unit root methodologies based on the least squares regression method.

Keywords: Quantile autoregression, nonparametric test, asymmetry, stock exchange, asset pricing

1. Introduction

The Efficient Market Hypothesis (EMH), introduced by Fama (1970), asserts that according to classical finance theory, information is rapidly incorporated into all asset prices, preventing participants from achieving returns surpassing the market return. However, over the last fifty years, various anomalies have been identified, including weekend, end-of-day, herd psychology, and trend effects, challenging the foundations of the EMH. Psychologists and experimental economists have argued that behavioural biases such as overconfidence, overreaction, and regret play a role in human decision-making under uncertainties. In their study, Grossman and Stiglitz (1980) criticize the efficient market hypothesis, contending that truly efficient markets, where information is perfectly known by everyone, do not exist. Grossman (1976) and Grossman and Stiglitz (1980) suggest that if markets were genuinely efficient, there would be no profitable investments resulting from information asymmetry among investors. The literature reflects a lack of consensus between advocates of information efficiency and behavioural finance, with ongoing theoretical and empirical studies. As emphasized by Bernstein (1999), the market equilibrium central to the EMH rarely occurs in practice, and market efficiency is better defined by evolutionary processes. Given the increased access to information in recent years, there is a growing importance in studies focusing on theoretical and empirical models related to information supply and information demand in information flow.

Shocks resulting from news flow to the markets and their persistence play a crucial role in financial asset forecasting models. In the finance literature, the unit root hypothesis is considered the primary method for assessing the permanence of shocks on financial variables. This hypothesis relies on an autoregressive process designed for optimal performance under the assumption of normality. However, given that variables in financial markets often exhibit a heavy-tailed (leptokurtic) distribution, it is crucial to employ estimation and inference procedures that produce robust results against deviations from the normality assumption. In classical regression, one assumption for the least squares estimators to be effective is that the series follows a normal distribution. Recognizing the need for robust estimators under deviations from normality, quantile unit root tests robust to such deviations, based on quantile autoregression, have been introduced to the literature. These tests are designed to exhibit strong power across various error distributions. Koenker and Xiao (2004) propose new tests for the unit root hypothesis based on the quantile autoregression (QAR) approach in a univariate context. Unlike standard unit root tests applied to examine the Efficient Market Hypothesis (EMH), which generally focuses on the average behaviour of stock prices, these quantile-based tests consider the impact of shock magnitudes and signs on the index.

This study proposes a quantile autoregression approach to assess market efficiency, establishing a connection between the types of news (good and bad) entering the market and their quantiles. By modelling stock market returns across various quantile levels, on the magnitude and sign of the shocks, the study reveals different market conditions. The aim is to investigate the persistence of shocks in the same series at different frequencies (daily, weekly, monthly, quarterly, annual) and explore the series' asymmetric dynamic structure. Consequently, instead of treating the series as a whole, it undergoes examination through classification based on shock magnitude and sign. This study represents the first to provide robust quantile autoregression evidence for the efficiency of the Borsa Istanbul stock index. The empirical analysis delves into market activity at different frequencies over the long term. Moreover, the study is poised to contribute to future research on optimal portfolio creation, leveraging both linear and non-linear quantile autoregressive processes. Additionally, the exploration of asymmetric dynamics holds significant implications for asset pricing models.

The persistence of good or bad news in the market holds significant importance for predicting price movements in stock markets. Quantile unit root tests, grounded in the quantile autoregression process, play a crucial role in forecasting price movements. These tests enable the examination of shock magnitudes and asymmetry caused by good and bad news separately, offering a nuanced perspective beyond treating the series as a whole. Methods for detecting the presence of a unit root in semi-parametric time series models are subject to ongoing theoretical and empirical exploration. One approach to enhance power performance involves the utilization of robust estimators. The literature provides a theoretical foundation encompassing methods robust to deviations from assumptions. Notable among these are studies on M estimation and inferences (Cox and Llatas, 1991; Knight, 1991; Phillips, 1995; Lucas, 1995; Rothenberg and Stock, 1997; Juhl, 1999; Xiao, 2001). The theoretical discourse on the quantile regression method and subsequent robust estimators initiated by Koenker and Bassett (1978) continues, with contributions from scholars such as Weiss (1987), Knight (1989), Koul and Saleh (1995), Koul and Mukherje (1994), Hercé (1996), Hallin and Jureckova (1999), and Rogers (2001).

Tests based on quantile autoregression provide valuable insights into the dynamics and persistence of financial time series. There are t-ratio, Kolmogorov-Smirnov, and Cramer von Mises type tests, relying on the estimation of selected quantiles within specific series intervals. OLS regression estimates lose their effective predictive properties when deviations from the normality assumption occur. In such instances, estimators based on quantile autoregression emerge as robust alternatives. However, when the normality assumption holds, the application of quantile regression results in a loss of efficiency. Furthermore, quantile unit root tests demonstrate enhanced power in the presence of asymmetric dynamics compared to classical unit root tests.

In the finance literature, various models explain empirical momentum and reversal phenomena, attributing them to stock prices under- or overreacting to good or bad news. Barberis, Shleifer, Vishny (1998) propose an investor sensitivity model where they assume returns to be a random walk, but investors are unaware of this, leading to poor stock price reactions to earnings announcements. Baur et. al. (2012) examine positive dependency (negative return) in lower quantiles and negative dependence (positive return) in upper quantiles. Engle and Manganelli (2004) introduce Conditional autoregressive value at risk (CAViaR), a VaR model based on quantile regression. Feng, Chen, Bassett

(2008) and Ma, Pohlman (2008) introduce quantile momentum measurements for creating momentum portfolios in asset management. Quantiles are increasingly utilized in optimal portfolio selection, as demonstrated by Chambers (2009), Bhattacharya (2009), Giovannetti (2013), and de Castro and Galvao (2019). Bassett and Chen (2002) examine the quantile regression method as an addition to the style classification toolkit, enhancing portfolio style classification by identifying the impact of style on the conditional return distribution beyond the expected value. Ma & Pohlman (2008) address issues in equity return forecasting and portfolio construction, introducing quantile regression methods to improve forecasting and portfolio outcomes. Quantile portfolio models aimed at modelling economic behaviour have been used by Chambers (2007), Bhattacharya (2009), Giovannetti (2013), and de Castro and Galvao (2019). Literature on optimal portfolio allocation includes studies by Kulldorff (1993), Föllmer and Leukert (1999), He and Zhou (2011), and Brown and Sim (2009). Castro et. al.'s (2022) study introduces a model for optimal portfolio allocation that maximizes the τ-quantile of portfolio return for $\tau \in (0, 1)$, addressing the preferences of investors with quantitative inclinations. The increasing importance of the quantile approach in portfolio selection is evident in the literature.

In Bahmani et. al. (2016) study, weekly stock prices data from eight countries with transition economies (Bulgaria, Croatia, Czech Republic, Hungary, Lithuania, Poland, Romania, and Russia) during the period 2000–2015 are utilized. The weak form of the market hypothesis is tested using the quantile unit root test, revealing that stock markets are weak-form efficient for most countries, except Bulgaria, Romania, and Russia. Novak (2019) employs the quantile autoregression approach to assess the market efficiency of the Croatian stock market, analysing daily CROBEX returns from 2000 to 2019. The study rejects the basic hypothesis when examining the weak form of market efficiency with quantile unit root tests. The observed ineffective predictable behaviour of CROBEX suggests the potential for investors to achieve abnormal profits. Jiang and Li's (2020) study introduces a new measure of market efficiency to analyse efficiency dynamics across various quantile levels in Chinese, Japanese, and US stock markets. The findings indicate that Japanese and US stock markets exhibit efficiency under normal conditions (mid quantiles) rather than during bull market (high quantiles) or bear market (low quantiles) conditions. In contrast, the Chinese stock market is deemed inefficient across all quantiles, with the US stock markets showing smaller deviations from efficiency in most periods. Nartea (2021) examines the stationarity of daily real stock prices in 12 Asia-Pacific countries (Australia, China, Hong Kong, Indonesia, Japan, Malaysia, New Zealand, Philippines, Singapore, South Korea, Taiwan, and Thailand) from 1991 to 2020. The results suggest overall stability in stock prices in higher quantiles. Furthermore, there is evidence of asymmetry in stock price dynamic adjustments in the upper deciles, where larger shocks are associated with faster mean reversion, and conversely, smaller shocks are linked to nonstationarity. There are also studies in the literature that measure the degree of asymmetry in the return-volatility relationship with quantile regression (Agbeyegbe, 2015; Badshah, 2013; Badshah et. al., 2016; Bekiros et. al., 2017).

In the financial and economic literature, the persistence of shocks is typically characterized by the unit root hypothesis. Traditional unit root tests for Borsa Istanbul have been commonly employed in studies (Özdemir, 2022). The literature indicates that standard unit root tests primarily focus on the average behaviour, neglecting the magnitude and signs of shocks. These tests assume a constant rate at which stock prices adjust toward equilibrium, irrespective of the shock's size or sign. Consequently, when the assumptions of traditional unit root tests are not met in financial markets, the rejection of the unit root fundamental hypothesis tends to be limited. Studies in the literature underscore that information efficiency is lower in emerging markets. This emphasizes that, especially in emerging markets like Turkey, where low-frequency information collection and processing costs are higher, the lower information efficiency leads to a more extended period for information to be fully reflected in asset prices.

The remainder of this study are structured as follows: Chapter 2 introduces the QAR model along with new tests and robust inferences based on QAR. Section 3 presents the data, while Section 4 assesses the results of the empirical analysis. Finally, Section 5 offers concluding remarks.

2. Methodology

Considering the heavy-tail behaviour often observed in financial time series in various empirical studies, it becomes crucial to utilize estimation and inference procedures that are robust to deviations from Gaussian conditions in non-stationary time series. The quantile regression approach becomes particularly relevant in this context, as it allows researchers to explore a range of conditional quantitative functions rather than focusing solely on a conditional measure of central tendency. Quantile autoregression methods offer a robust framework for inference, enabling the investigation of various forms of conditional heterogeneity by exploring different conditional quantiles. The quantile unit root test proposed by Koenker and Xiao (2004) introduces new tests based on quantile autoregression. These tests evaluate statistics on selected quantiles or over a specific range of quantiles, utilizing estimations based on t-ratio tests, Kolmogorov-Smirnov, or Cramer-Von Mises type tests. Notably, these new tests provide robust results even in the absence of normality assumptions, addressing a broader set compared to existing methods in the literature. While the quantile unit root test demonstrates good power under non-normal conditions, its effectiveness diminishes when applied under normality conditions. Furthermore, quantile unit root tests facilitate the examination of asymmetric dynamics and exhibit superior power compared to classical unit root tests (Koenker-Xiao, 2006). Before delving into the quantile autoregressive process, it is essential to consider the ADF (Dickey-Fuller, 1979) regression model, an extension of the first-order autoregression model of the unit root process.

$$y_t = \alpha_1 y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1} \Delta y_{t-j} + u_t \tag{1}$$

The autoregressive coefficient α_1 in the equation above plays a crucial role in assessing persistence, serving as an indicator for the presence of a unit root in financial time series. Specifically, if α_1 equals 1, the series contains a unit root, signifying persistence in the process. Conversely, If $|a_1| < 1$ situation occurs, the process is stationary. Introducing the σ- region produced by $\{u_s,\ s £ t\}$ via F_t, the conditional quantile t. of y_t on F_{t-1} is defined as follows:

$$Q_{y_t}(\tau \,/\, \mathcal{F}_{t-1}) = Q_u(\tau) + \alpha_1 y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1} \Delta y_{t-j} \tag{2}$$

In the above equation, for j=1,...,q when it is defined as

$$Q_u(\tau) = \alpha_0(\tau), \alpha_j = \alpha_j(\tau) \tag{3}$$

$$\alpha(\tau) = (\alpha_0(\tau), \alpha_1(\tau), \dots, \alpha_{q+1}(\tau))', x_t = (1, y_{t-1}, \Delta y_{t-1}, \dots, \Delta y_{t-q})', \tag{4}$$

we obtain the following equation:

$$Q_{y_t}(\tau \,/\, \mathcal{F}_{t-1}) = x_t' \alpha(\tau) \tag{5}$$

Here, the estimation of the linear quantile autoregression model includes a solution to the following minimization problem.

$$\min_{\alpha \,\epsilon\, \mathbb{R}^2} \sum_{t=1}^{n} \rho_\tau (y_t - x_t^T b) \tag{6}$$

Here, the ρ_τ function is the piecewise control function shown as $\rho_\tau(u) = u(\tau - I(u < 0))$ proposed by Koenker and Bassett (1978). With $0 < \tau < 1$, the I function as an indicator function is as follows:

$$\rho_\tau(u) = \begin{cases} \tau|u|, & u \geq 0 \\ (1-\tau)|u|, & u < 0 \end{cases} \tag{7}$$

The τ quantile with 0<τ<1 is defined as the solution to the minimization problem:

$$\min_{b \,\in\, \mathbb{R}^K} \left[\sum_{t \,\in \{t: y_t \geq x_t b\}} \tau |y_t - x_t b| + \sum_{t \,\in \{t: y_t < x_t b\}} (1-\tau) |y_t - x_t b| \right] \tag{8}$$

The minimization problem yields the solution attributed to $\hat{\alpha}(\tau)$, representing the τ. quantile autoregression process viewed as a function of τ. The estimation of the conditional density function of y_t is accomplished through the difference quotients for selected quantiles of τ.

$$\hat{f}_{y_t}(\tau / x_t) = (\tau_i - \tau_{i-1}) / (\, \hat{Q}_{y_t}(\tau_i / x_t) - \hat{Q}_{y_t}(\tau_{i-1} / x_t)) \tag{9}$$

The approach based on the quantile autoregression process offers a more robust method for testing the unit root hypothesis compared to traditional unit root tests relying on least squares. Koenker-Xiao's (2004) t-ratio test statistic is defined as:

$$t_n(\tau) = \frac{f\big(\widehat{F^{-1}(\tau)}\big)}{\sqrt{\tau(1-\tau)}} (Y_{-1}^T P_X Y_{-1})^{1/2} (\widehat{\alpha_1}(\tau) - 1). \tag{10}$$

$f\big(\widehat{F^{-1}(\tau)}\big)$ is the consistent estimator of $f\big(F^{-1}(\tau)\big)$. Y_{-1} is a vector consisting of lagged values of the dependent variable (y_{t-1}) and P_X is the projection matrix onto the space orthogonal to $X =$

$(1, \Delta y_{t-1}, \dots, \Delta y_{t-q})$. The sparsity function s(τ) is defined in two ways: (1) inverse of the density function or (2) derivative of the quantile function:

$$s(\tau) = F^{-1\prime}(\tau) = 1/f\left(F^{-1}(\tau)\right) \tag{11}$$

Here is relevant literature on $f\left(F^{-1}(\tau)\right)$ estimation, including the studies of Siddiqui (1960) and Bofinger (1975):

$$f_n\left(F_n^{-1}(\tau)\right) = \frac{2h_n}{F_n^{-1}(\tau + h_n) - F_n^{-1}(\tau - h_n)} \tag{12}$$

$F_n^{-1}(.)$ is an estimator approximation of $F^{-1}(.)$ where h_n is a bandwidth that approaches 0 as n→∞. The bandwidth used in this study is the Bofinger (1975) bandwidth as commonly adopted in the literature:

$$h_B = n^{-1/5}\left[\frac{4.5\phi^4(\Phi^{-1}(\tau))}{[2(\Phi^{-1}(\tau))^2 + 1]^2}\right]^{1/5} \tag{13}$$

Here, the functions $\phi(.)$ and $\Phi(.)$ represent the density and cumulative distribution functions of the standard normal distribution, respectively.

At any chosen τ, the test statistic $t_n(\tau)$ is the quantile regression counterpart of the ADF t-test statistic based on least squares regression. Unit root tests based on quantile autoregressive processes can be formed by representative quantiles (low quantile, median, high quantile). Alternatively, the examination can cover the range of selected quantiles with $\tau \in \mathcal{T}$. Another approach is to test over a range of quantiles rather than just focusing on selected ones. The Kolmogorov-Smirnov (KS) test based on the quantile regression process for τ ∈ T is as follows:

$$QKS_t = \sup_{\tau \in \mathcal{T}} |t_n(\tau)| \tag{14}$$

with $\tau_0 > 0$, $\tau \in \mathcal{T} = [\tau_0, 1 - \tau_0]$.

In applications, $t_n(\tau)$ can be calculated with $\{\tau_i = i/n\}_{i=1}^{n}$. Thus, the QKS_t statistics can also be generated by taking its maximum on $\tau_i \in \mathcal{T}$. Evaluation can be made not only for the selected quantiles (t) by comparing the calculated $t_n(t)$ test statistic with the critical values, but also by comparing the Quantile Kolmogorov-Smirnov (QKS) test and its critical value for the series in general. While the limiting distributions of both $t_n(\tau)$ and QKS tests are not standardized, Koenker and Xiao (2004) suggest using a resampling procedure (bootstrap number = 10,000 in our study) to approximate small sample distributions.

Thus, states can be examined for some quantiles, such as various decimals. The practical importance of this feature can be examined, as different quantiles correspond to shocks of different signs and magnitudes. Thus, asymmetric effects are observed when examining the persistence of shocks.

3. Data

In this study, which examines the asymmetric dynamics of the BIST100 index on a quantile basis, daily, weekly, monthly, quarterly, and annual closing indices covering the period between March 2003 and March 2023 are used. It is used by taking the natural logarithm of the index data.

Descriptive statistics are as follows:

Table 1: Descriptive statistics

	Daily	Weekly	Monthly	Quarterly	Annual
Mean	6.4654	6.468	6.4762	6.4739	6.6537
Median	6.5614	6.5622	6.5755	6.5473	6.5755
Standard dev.	0.7196	0.7192	0.7304	0.7517	0.8649
Kurtosis	0.7587	0.7674	0.8934	1.0885	0.9832
Skewness	-0.0131	-0.0066	0.0513	0.0826	0.8138
JB prob.	0.0000	0.0000	0.0000	0.0000	0.0000
Min	4.4878	4.544	4.5513	4.5513	5.2271
Max	8.6414	8.6142	8.6142	8.6142	8.6142
Obs.	5024	1042	241	81	21

When we look at the descriptive statistics in Table 1, there is a minimal increase in the mean, median and standard deviation values as we go from the daily data to the annual data. When the kurtosis and skewness are examined for the assumption of normality, it is seen that the series are not normally distributed. In addition, as seen from the JB probability values, the null hypothesis of normal distribution is rejected. The numbers of observation values are 5024, 1042, 241, 81, and 21 for daily, weekly, monthly, quarterly, and annual frequencies, respectively.

4. Findings

In this section, we present the results of the Augmented Dickey-Fuller (ADF) and Koenker-Xiao's (2004) quantile unit root tests conducted on the BIST100 index values at various frequencies. The quantile unit root test is applied across different deciles (0.1, 0.2, ..., 0.9) for the BIST100 index at daily frequencies, and critical values are determined using the Bootstrap method in Matlab.

Table 2 provides the quantile unit root test results for the daily frequency of the BIST100 index. While the ADF test suggests the presence of a unit root in the dataset, interestingly, the data is observed to be stationary at higher quantiles (specifically, [0.7, 0.8, 0.9]), leading to the rejection of the null hypothesis for daily data. This implies that the index tends to revert to the mean in response to good news, particularly at high quantiles. Conversely, a unit root process is detected in the face of medium and bad news, corresponding to medium and low quantiles in the stock market, respectively. However, when the ADF test statistics results for the data set for the period 2003-2023 are examined, we see that the series exhibits unit root in terms of the daily frequency data set.

Table 2: Koenker-Xiao (2004) Quantile Unit Root Test Results (daily)

τ (Quantiles)	Coefficient (α_1)	Results	$t_n(\tau)$	Critical Values
0.1	1.0029	1	4.5870	-2.7673
0.2	1.0027	1	5.7327	-2.8151
0.3	1.0022	1	5.5463	-2.7976
0.4	1.0012	1	3.6015	-2.7438
0.5	1.0003	1	1.0035	-2.6543
0.6	0.9997	1	-0.8421	-2.5635
0.7	0.9989	0	-3.0383**	-2.4450
0.8	0.9980	0	-5.0526**	-2.3800
0.9	0.9971	0	-4.6971**	-2.1245
QKS		0	5.7327**	2.7365
ADF		1	-0.0846	-2.8619

*Note: ** indicate 5% significance level.*

Table 3: Koenker-Xiao (2004) Quantile Unit Root Results (weekly)

τ (Quantiles)	Coefficient (α_1)	Results	$t_n(\tau)$	Critical Values
0.1	1.0039	1	1.0764	-2.5720
0.2	1.0027	1	1.0090	-2.6507
0.3	1.0004	1	0.1815	-2.6987
0.4	0.9993	1	-0.3892	-2.6338
0.5	0.9999	1	-0.0507	-2.5974
0.6	0.9984	1	-0.9339	-2.5746
0.7	0.9980	1	-1.0821	-2.5322
0.8	0.9986	1	-0.7240	-2.4507
0.9	0.9960	1	-1.4525	-2.5116
QKS		1	1.4525	2.7834
ADF		1	-0.1257	-2.8641

*Note: * indicate 5% significance level.*

Table 4: Koenker-Xiao (2004) Quantile Unit Root Results (monthly)

τ (Quantiles)	Coefficient (α_1)	Results	$t_n(\tau)$	Critical Values
0.1	0.9930	1	-0.5402	-2.6102
0.2	1.0121	1	1.1838	-2.4517
0.3	1.0000	1	0.0000	-2.5292
0.4	0.9965	1	-0.3335	-2.5692
0.5	0.9835	1	-1.6278	-2.6105
0.6	0.9880	1	-1.3749	-2.5390
0.7	0.9922	1	-0.9167	-2.5587
0.8	0.9929	1	-0.8101	-2.5772
0.9	0.9949	1	-0.2970	-2.5309
QKS		1	1.6278	2.8144
ADF		1	-0.4413	-2.8734

Tables 3, 4, and 5 display the results of the quantile unit root tests conducted on the weekly, monthly, and quarterly frequencies of the BIST100 index. The findings reveal that, across all quantiles, the series exhibits the presence of a unit root for the weekly, monthly, and quarterly frequencies of the BIST100 index. This observation is consistent with the results of the Augmented Dickey-Fuller (ADF) test statistics. The ADF test statistics consistently indicate the presence of a unit root in the dataset covering the period 2003-2023 for weekly, monthly, and quarterly frequencies.

Table 5: Koenker-Xiao (2004) Quantile Unit Root Test Results (quarterly)

τ (Quantiles)	Coefficient (α_1)	Results	$t_n(\tau)$	Critical Values
0.1	1.0098	1	0.1505	-2.1582
0.2	0.9897	1	-0.247	-2.5293
0.3	0.9715	1	-1.1061	-2.4361
0.4	0.9623	1	-1.3332	-2.5912
0.5	0.9665	1	-1.3947	-2.7262
0.6	0.9602	1	-1.4543	-2.7244
0.7	0.9765	1	-0.6682	-2.3657
0.8	0.9538	1	-1.2449	-2.5363
0.9	1.0294	1	0.3413	-2.5642
QKS		1	1.4543	2.7913
ADF		1	-0.4773	-2.8981

*Note: * indicate 5% significance level.*

Table 6: Koenker-Xiao (2004) Quantile Unit Root Test Results (annual)

τ (Quantiles)	Coefficient (α_1)	Results	$t_n(\tau)$	Critical Values (5%)
0.1	1.7759	0	-3.9763**	-2.1200
0.2	1.3871	1	2.4879	-2.1714
0.3	1.3423	1	1.6594	-2.1200
0.4	1.4961	1	2.6142	-2.2774
0.5	1.0828	1	0.4413	-2.2122
0.6	1.0883	1	0.3226	-2.342
0.7	1.1175	1	0.6050	-2.2455
0.8	1.0349	1	0.1682	-2.5438
0.9	1.5645	0	-4.3457**	-2.5095
QKS		0	4.3457**	2.7580
ADF		1	1.587801	-3.0404

*Note: ** indicate 5% significance level.*

While the annual series shows evidence of a unit root according to the ADF test results, the quantile unit root test (Table 6) reveals that both the highest [0.9] and the lowest [0.1] quantiles are stationary. This implies that the index tends to revert to the mean in response to extreme quantiles, representing the best and worst shocks corresponding to good and bad news. It's worth noting that, due to the annual closing data neglecting numerous observations, results become more reliable as we move closer to daily frequencies.

5. Conclusions

This study investigates the dynamic structure of the Borsa Istanbul index using the linear quantile unit root test and provides insights into its long-term effectiveness. The heavy-tail distribution of the data raises concerns about the efficacy of traditional linear unit root tests, prompting the need for an alternative approach to ensure robust inference in non-normal distributions. The quantile regression method enables researchers to explore a range of conditional quantile functions, offering a more comprehensive understanding of conditional heterogeneity. Quantile unit root tests, based on quantile autoregression, have demonstrated strong performance in finite samples, as evidenced by Monte Carlo simulations that highlight substantial power gains. Particularly in the presence of a non-normal, heavy-tailed distribution, quantile unit root tests exhibit greater robustness compared to conventional OLS-based unit root tests. Hence, in this study, we apply the Koenker-Xiao (2004) linear quantile unit root test, serving as the quantile counterpart to the ADF test.

The quantile unit root tests offer a unique opportunity to scrutinize the dynamics of a series based on both the magnitude and sign of shocks. The results clearly indicate that the quantile unit root test provides more robust evidence in favour of stationarity compared to classical unit root tests. Analysing the daily frequency results reveals the presence of noticeable asymmetric dynamics. Notably, good news in the stock market exhibits a temporary, stationary process, while bad news displays a persistent, unit root behaviour. This observed asymmetry aligns with expectations for emerging market stock markets. Encompassing a broad timeframe from 2003 to 2023 and encompassing various shocks, this study recognizes the limitations of relying on a single statistical measure to summarize the entire period.

Utilizing the quantile autoregression process, quantile unit root tests allow for a nuanced understanding of asymmetric dynamics in response to both good and bad news, accounting for variations in shock magnitudes.

The results from the quantile unit root test indicate that daily data exhibits a unit root in low quantiles, suggesting that good news has a temporary effect, while high quantiles appear to be stationary, indicating persistent behaviour in response to bad news. This asymmetric dynamic reveals the nuanced nature of the stock market's reaction to different news types. In the Quantile Kolmogorov-Smirnov (QKS) test statistic, $t_n(\tau)$ is considered as the absolute supremum across all quantiles, leading to the conclusion of stationarity when compared to the critical value. Koenker-Xiao's (2004) quantile unit root test, unlike the daily stock market index, shows unit root presence across all quantiles for weekly, monthly, and quarterly frequencies. For the annual series, stationarity is observed in the highest and lowest quantiles, indicating a tendency for the extreme news deciles of that period to revert to the mean. However, it's worth noting that the annual closing data may not capture as many shocks throughout the year, making daily data a more realistic source of information.

The results clearly demonstrate distinct outcomes between the first and last quantiles, highlighting the asymmetry and magnitude of shocks. While bad news (first quantiles) exhibits persistence in the market, indicating a persistency effect, good news (last quantiles) shows a temporary impact, with the series tending to revert to the mean. This asymmetry in the response to good and bad shocks underscores the importance of examining various quantiles and deciles.

Quantile autoregression allows for a nuanced examination of the asymmetry and magnitudes in the persistence of shocks, offering insights into how positive and negative shocks influence the stock market or assets. By identifying the shocks corresponding to specific quantiles, we can assess whether the unit root behaviour changes under different economic conditions. Additionally, recognizing and understanding asymmetry becomes crucial in the context of asset pricing within the securities market.

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FUNDING AND OVERFUNDING PHENOMENA IN CROWDFUNDING: RELEVANCE OF PLATFORM CHOICE AND VARYING INDUSTRY DYNAMICS

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Abstract

This study provides new evidence on factors relevant to the success of crowdfunding campaigns run in Europe between 2015 and 2017 on the most popular crowdfunding platforms in Germany/Austria – Kickstarter.com and Startnext.com. In particular, for this study, a sample of 10,514 campaigns from Germany and Austria for the first time serves as a basis for identifying the determinants of the level of projects' (over-)funding. For crowdfunding projects, an increase in a project's funding goal results in higher funding on both platforms, but this does not guarantee success, i.e. reaching the relevant funding goal. Projects with a higher success probability show lower funding goals, especially if launched on Startnext.com. In contrast, a longer duration negligibly increases the amount raised on Startnext and slightly decreases on Kickstarter. On Startnext, projects from the Art cluster have a higher chance to succeed, while those from the Technology cluster show smaller success probabilities as they regularly get less funding. On Kickstarter, projects from the Art, Technology, or Lifestyle field reach higher financing as compared to the Sustainability area. We show that the uncertainty about market size and project/founder quality leads to diverging over- and underfunding levels across platforms and industry clusters, which is of core importance to interested stakeholder groups.

Keywords: crowdfunding, crowd, reward, Kickstarter, Startnext

1. Introduction

Crowdsourcing offers the possibility for individuals and founders to fund their projects, products, non-profit and business ideas with small contributions of money from many individuals using internet platforms. As a financing option, it is especially important for those who lack savings or have only limited access to funds from family, friends, or traditional forms of financing such as bank lending, business angel (BA), and venture capital (VC) investments. The popularity of crowdfunding considerably increased – in 2017 a total of 34 billion was raised globally by crowdsourcing projects with 10.4 billion EUR only in Europe (Startnext (2020)).

The rise of interest in this form of financing also resulted in an increased amount of research on the factors leading to the success of crowdfunding campaigns, e.g. Mollick (2014), Crosetto and Regner (2014)), Koch and Siering (2015), Gierczak at el., (2016), Barbi and Bigelli (2017) and Rossi and Vismara (2018). This study focuses on donation- and reward-based crowdfunding which, in contrast to equity- and lending-based crowdsourcing, does not provide an incentive for making a financial return. In particular, this research aims to describe the size of crowdfunding projects' overfunding in different industries spanning from arts to technology. Overfunding describes the amount of money provided by the crowd above the – project realization required – funding goal the project initiator was asking for. Moreover, the associated determinants of the level of overfunding for crowdfunding campaigns run in Europe on the Kickstarter and Startnext platforms between 2015-2017 based on the population of more than 10,000 projects are shown. The drivers of success may have a changing impact in several industry categories or/and this effect might be also different across the two analysed platforms, e.g. due to unknown market size (Strausz (2017)). Crowdfunding literature neither controls for industry-specific effects, nor for platform-specific dynamics. We want to close this research gap.

Kickstarter.com is the world's largest platform for crowdfunding based on the amounts pledged (Kickstarter.com), while Startnext.com remains its' main counterpart in German-speaking countries (Startnext.com). For this study, a hand-collected sample of 10,514 crowdfunding campaigns from Germany and Austria for the first time serves as a basis for identifying the determinants of the level of projects' (over-)funding, i.e. success, through OLS, Logit, Probit, and ML regressions including the Heckman correction for sample selection.

In sum, we find evidence that the choice of a particular platform affects the chances for success of a project seeking crowdfunding in Germany or/and Austria. The main reasons for diverging levels of funding remain the uncertainty about the final demand or/and project quality as suggested by Strausz (2017). Kickstarter and Startnext act as the most important crowdfunding platforms for German and Austrian projects, thus, understanding the differences between success factors is important for regionally and internationally active founders, supporters or funders, SMEs, investors, and their advisors.

In the following, we present a background on crowdsourcing in section 2, a literature review on success factors in crowdfunding in section 3, and data in section 4. In section 5, the levels of (over-)funding across various industry categories and platforms are documented. Finally, the determinants leading to successful crowdfunding of European projects stemming from two popular platforms are discussed, before the conclusion follows in section 6.

2. Background on Crowdfunding

Crowdfunding can be seen as an informal pre-BA or VC financing form. It allows project founders to directly ask a broad public to support their innovative ideas, projects, or product developments and sales (Kuppuswamy and Bayus (2013)). However, the idea of crowdfunding is to obtain, i.e. funds, money, goods, or time, from a broad public where each individual provides an affordable or minimal amount instead of raising the money from a small group of sophisticated investors (Belleflamme et al. (2012)). It can, therefore, be defined as an open call for collecting resources from the population via an online platform. In return for the contributions, the crowd can receive several tangible or intangible assets like experiences, which depend on the type of crowdfunding (Delivorias (2017)). Strausz (2017) adds that interaction between initiators and investors before investment screening for valuable projects on crowdfunding platforms is improved under aggregate demand uncertainty. Generally, several types of crowdfunding campaigns differ in their purpose and are either non-profit or for-profit projects. Four categories of campaigns are most commonly observed (Delivorias (2017)):

- donation-based (crowdsponsoring or crowdfunding) where supporters do not receive any rewards for their contributions,
- reward-based (crowdfunding) where backers receive gifts, experiences, goods, or services in exchange for their monetary support,
- lending-based (crowdlending) where funders receive at least an attractive interest payment in exchange for financing an idea or project.

- equity-based (crowdinvesting) where investors typically receive shares in the financed venture in exchange for their contributions.

Given the variety of launched projects, the supporters and investors in crowdfunding often have different motivations for supporting them. According to Gierczak et al. (2016), these motivations can be described as altruistic (focused on projects benefitting the society, mainly non-profit), hedonistic (associated with projects delivering essential goods, also creative and innovative, or/and satisfying the needs for pleasure) and profiting (guaranteeing a return for financial investments via, i.e. interests, revenue/profit-sharing arrangements or equity stakes). In this study, we focus on donation- and reward-based crowdfunding as these two forms do not provide incentives for financial investment returns to occur but have reached a high level of popularity and serve an important role for the broad audience. Most of the research carried out on the topic was published in the last ten years as data became available and will be presented next.

3. Research on Success Factors in Crowdfunding

Prior studies provide support to the notion that there are important factors leading to success – reaching the funding goal or/and building up overfunding. Table 1 summarises the major findings in a concise manner.

In crowdfunding, many campaigns fail by significant amounts, while those that succeed mainly succeed by small amounts. According to Mollick (2014), the project itself needs to be convincing and the popularity of the entrepreneur through social networks is impacting success (e.g. Aleksina, Akulenka and Lubloy (2019), Dalla Chiesa (2021) and Tosetto, Cox and Ngyuen (2022)). Additionally, project quality can be inferred on Kickstarter.com from the project description that is offered on the campaign webpage, especially its depth (Koch and Siering (2015)). In this context, information relevance and comprehensiveness are influencing information usefulness and adoption by an online consumer community (Cheung et al. (2008)). The use of specific phrases, e.g. emotional text passages, on the campaign page profoundly influences project success (Mitra and Gilbert (2014), Koch and Siering (2019) and Song et al. (2019)). Furthermore, project presentation – including videos and pictures about the underlying idea – is paramount to the success of a crowdfunding project. According to Kuppuswamy and Bayus (2013), videos play a pivotal role in increasing the success of a crowdfunding campaign which is also confirmed by research conducted by Barbi and Bigelli (2017). This is because supporters want as much information as quickly as possible. Offering more details lowers the information asymmetry and reduces the perceived riskiness of a project. This means that high-quality projects are identified easily by the supporters, who prefer projects with superior return/risk profiles (Bento, Gianfrate and Groppo (2019)).

In addition, the consensus from different authors is that setting a high funding goal decreases the probability of a project being funded (Crosetto and Regner (2014), Cordova and Gianfrate (2015) and Barbi and Bigelli (2017)) or leads to project failure (Patel and Devaraj (2016)). In general, successful projects tend to have a much lower funding target in comparison to unsuccessful or cancelled projects (Frydrych et al. (2014)). According to Forbes and Schaefer (2017) beyond campaign failure also a second problem arises if the funding goal is reached and results in unachievable expectations that the entrepreneur cannot meet. Thus, the founders should be motivated to choose a funding goal for the campaign reflecting the activities that will be carried out and the management capabilities of the respective team. Self-pledges decrease the amount of available money (Crosetto and Regner (2018), but lead to better post-campaign performance (Crosetto and Regner (2021)). Research has found conflicting results when it comes to the duration of a campaign. The longer (shorter) the fundraising timeframe is, the higher (higher) the likelihood that contributions will add up to an amount equal to or above the funding goal according to Cordova et al. (2015) and Mendes-Da-Silva (2016) (Frydrych et al. (2014)). Kuppuswamy and Bayus (2013), Crosetto and Regner (2014) and Barbi and Bigelli (2017) also conclude that a shorter campaign increases success chances. However, nonlinear relationships, e.g. U-shape, could explain the existing differences.

Table 1: An Overview of Previous Crowdfunding Research

Author(s)	Dimensions Discussed	Correlation to Success
Mollick (2014)	project itself	Positive
Koch and Siering (2015)	higher depth of the project description	Positive
Cheung, Lee, and Rabjohn (2008)	relevant and comprehensive information	Positive
Mitra and Gilbert (2014)	using specific language phrases	Positive
Kuppuswamy and Bayus (2013), Barbi and Bigelli (2017)	presence of a video presentation	Positive
Xu et al. 2014, Rossi and Vismara (2018)	more updates (especially in crowdinvesting)	Positive
Crosetto and Regner (2014), Frydrych, Bock, Kinder, and Koeck (2014), Cordova and Gianfrate (2015), Patel and Devaraj (2016), Barbi and Bigelli (2017) and Forbes and Schaefer (2017).	relatively low/appropriate funding goal	positive
Cordova et al. (2015)	higher duration	positive
Kuppuswamy and Bayus (2013), Crosetto and Regner (2014), Frydrych et al. (2014) and Barbi and Bigelli (2017)	shorter duration	positive
Kuppuswamy and Bayus (2013) and Barbi and Bigelli (2017) versus opposite finding Shengsheng, Xue, Ming, and Jiayin, (2014)	more reward levels	positive
Crosetto and Regner (2014) and Forbes and Schaefer (2017)	pre-selling of products/rewards	positive
Koch (2016) and Borst, Moser and Ferguson (2018)	highlighted on a crowdfunding platform	positive
Mollick (2014), Lu, Xie, Kong and Yu (2014), Koch (2016) and Borst, Moser and Ferguson (2018)	the popularity of the initiator and social media impact on crowdfunding	positive
Zvilichovsky, Inbar and Barzilay (2013), Siering and Koch (2015)	initiator's engagement in other crowdfunding projects	positive
Belleflamme, Lambert and Schwienbacher (2010)	non-profit projects versus for-profit ideas	positive
Aleksina, Akulenka and Lublóy (2019)	Professional contact, tweet, retweet	positive
Bento, Gianfrate and Groppo (2019)	projects with superior return/risk profiles.	positive
Berns, Jia and Gondo (2022)	communication	positive
Dalla Chiesa (2021)	Social networks	positive
Crosetto and Regner (2018), Crosetto and Regner (2021)	Self-pledges	positive
Song et al. (2019)	Text passages	positive
Tosetto, Cox and Ngyuen (2022)	Social ties (Email, Facebook, Twitter) and project description	positive
Koch and Siering (2019)	Text emotionality	positive
Koch, Lausen and Kohlhase (2021)	funding redistribution mechanism	positive
Mendes-Da-Silva et al. (2016)	Longer duration, shorter distance (close network)	positive
Otte and Maehle (2022)	Combinations of factors	positive
Rykkja, Munim and Bonet (2020)	Less complex cultural projects choose local Platforms	

Note: This table shows a selection of past studies discussing various success determinants.

Belleflamme et al. (2010) state that non-profit organizations and ideas tend to be more successful compared to their for-profit counterparts. Another important crowdfunding success factor is the use of various reward levels when presenting a project. Successful projects tend to have a larger number of reward levels (Kuppuswamy and Bayus (2013) and Barbi and Bigelli (2017)). Most probably, investors fund projects in exchange for the primary outcome, i.e. a product or service, and each reward level attracts a different group of investors. However, one can also be overdue as

Shengsheng et al. (2014). In the year 2014, Crosetto and Regner analysed funding dynamics, motivation, and success determinants based on Startnext data (October 2012 till February 2014) and found that offering product pre-sellings is key to a project's success. Backers are incentivized by the product that they will receive, thus, founders can price discriminate against different groups (Crosetto and Regner (2014)). The pre-selling and reward options should, however, be limited to avoid confusion during the campaign or delivery phase and managing obligations versus expectations (Forbes and Schaefer (2017)). Galkiewicz (2018) states that for Startnext and Kickstarter a comparably strong and medium effect of product offerings on the level of (over-)funding is only observable for projects from the Technology and Fashion category, respectively. The most common success factors highlighted in the literature are the choice of the funding goal, duration of a crowdfunding campaign, presentation of a video, reward levels, and the number of backed projects by the entrepreneur. The following empirical analysis aims to clarify whether the same factors matter on two popular crowdfunding platforms across different industries.

4. Data

Data Description. For this study a sample of 10,514 crowdfunding campaigns from Germany and Austria launched on the world's biggest crowdfunding platform Kickstarter and Startnext (the largest crowdfunding platform in Germany and Austria) serves as a basis for comparing the level of overfunding (Kickstarter.com, Startnext.com, and Galkiewicz and Galkiewicz (2018)). In particular, the information on the following variables is hand-collected as the webpage structure changes over time: project category (i.e. Art, Technology, etc.), subcategory (i.e. 3-D Printing), location of project´s founders, currency in which a project can be funded, total funding amount, initial funding goal (all successful projects obtain at least a funding as high as the funding goal), funding threshold, funding period start and end (funding period length for money collection), type of support (the means of reimbursement for backers for their contribution, e.g. no reward, gift, product), number of backers, number of new backers (those who contributed to the founder's project for the first time), number of returning backers (those who already backed a project of the founder), and number of comments on the project. The funding goals and funding amounts of projects from the Kickstarter platform are translated into EUR amounts by applying the respective average exchange rate in a year. Overfunding describes the amount of additional funding founders can use beyond the pre-specified funding goal of the project and is calculated by subtracting the funding goal amount from the finally obtained funding (overfunding = funding – funding goal).

Projects from both platforms belong to one of the following 25 categories: Agriculture, Art, Audio Book, Comics, Community, Crafts, Dance, Design, Education, Environment, Event, Fashion, Film & Video, Food, Games, Innovation, Journalism, Music, Photography, Publishing, Technology, Social Business, Sport, Technology or Theater. These categories are clustered into five different industry groups for the first time based on similarities presented by Galkiewicz and Galkiewicz (2018, 2019):

1. Art cluster: Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, Theater
2. Technology cluster: Education, Science, Innovation, Technology,
3. Sustainability cluster: Agriculture, Crafts, Community, Environment, Social Business,
4. Publishing cluster: Audio book, Comics, Journalism, Publishing,
5. Lifestyle cluster: Food, Games, Sport,

The collected and clustered variables are transformed for the purposes of the analysis in the following way: a dummy variable successful is created with values of 1 in case funding equals at least the funding goal, overfunding is created by subtracting the funding goal from the funding and for the cluster dummy variables are created. Table 2 and Table 3 shows the variables used in the study with the remaining definitions and descriptive statistics.

Table 2: **An Overview of Variable Names Used in the Study**

Variable Name – Part I	Variable Name – Part II
Successful (dummy variable with 1=success, 0 otherwise)	Funding (ln) (logarithmic value, dep. var.)
Funding Goal in EUR	Overfunding (ln) (logarithmic value, dep. var.)
Funding n EUR	Backers (ln) (logarithmic value, dep. var.)
Overfunding in EUR	Funding/Backer (ln) (logarithmic value, dep. var.)
Duration (in days)	Art_cluster_dv (dummy variable with 1=Art, 0 otherwise)
Backers (number)	Technology_cluster_dv (dummy variable with 1=Technology, 0 otherwise)
Funding/Backer (funding per backer)	Sustainability_cluster_dv (dummy variable with 1=Sustainability, 0 otherwise)
Austrian Location (dummy variable with 1=Austria, 0 otherwise)	Publishing_cluster_dv (dummy variable with 1=Publishing, 0 otherwise)
Platform (dummy variable with 1=Startnext (SN), 0=Kickstarter (KS))	Lifestyle_cluster_dv (dummy variable with 1=Lifestyle, 0 otherwise)
Funding Goal (ln) (logarithmic value, indep. var.)	

Advanced econometric techniques like Wilcoxon-Rank-Sum-Testing, Ordinary Least Squares (OLS), Logit, and Probit regression analyses allow identifying correlations between the aforementioned variables and the level of a project's overfunding, i.e. success, on the Startnext and Kickstarter platforms between 2015 and 2017 for the first time in such an extensive manner.

Table 3 presents a general overview of the data for each platform individually and in total. Reaching crowdfunding success is indicated by the dummy variable successful_dv, which shows a value of one for all the projects that reached their funding goal and a value of zero otherwise. For OLS regressions, the dependent variables are included in the form of the natural logarithm of the (over-)funding received or of the number of backers to enhance the quality of the results.

Table 3: **Startnext and Kickstarter Projects – A General Overview of the Sample**

Platform	Variables	N	sd	min	p25	mean	p50	p75	max
SN (1)	Successful	5747	0.50	0.00	0.00	0.55	1.00	1.00	1.00
	Funding Goal	5748	28212.61	15.00	2500.00	10378.73	5000.00	10000.00	1000000.00
	Funding	5748	17947.37	0.00	377.50	5487.69	2023.50	5660.00	801250.00
	Overfunding	3079	11182.52	1.00	120.00	2071.27	381.00	1208.00	417359.00
	Duration	5748	18.93	1.00	31.00	44.34	41.00	54.00	184.00
	Backers	5748	171.91	0.00	8.00	71.73	29.00	74.00	5504.00
	Funding/Backer	5748	210.14	0.00	33.48	84.04	53.90	90.40	11952.50
	Austrian Location	5748	0.27	0.00	0.00	0.08	0.00	0.00	1.00
	Platform (1=SN)	5748	0.00	1.00	1.00	1.00	1.00	1.00	1.00
	Funding Goal (ln)	5748	1.20	2.71	7.82	8.49	8.52	9.21	13.82
	Funding (ln)	5748	2.43	0.00	5.93	7.01	7.61	8.64	13.59
	Overfunding (ln)	3079	1.83	0.00	4.79	5.91	5.94	7.10	12.94
	Backers (ln)	5748	1.65	0.00	2.08	3.14	3.37	4.30	8.61
	Funding/Backer (ln)	5748	1.19	0.00	3.51	3.87	3.99	4.50	9.39

Platform	Variables	N	sd	min	p25	mean	p50	p75	max	
KS (2)	Successful	4765	0.42	0.00	0.00	0.22	0.00	0.00	1.00	
	Funding Goal	4766	1474893.00	1.00	2800.00	64791.10	10000.00	25000.00	100000000.00	
	Funding	4766	61937.74	0.00	10.00	9248.05	251.00	2764.00	3198516.00	
	Overfunding	1046	118479.40	1.00	205.00	23866.32	1196.00	6728.00	3148516.00	
	Duration	4766	11.67	3.00	30.00	34.56	30.00	38.00	61.00	
	Backers	4766	608.54	0.00	1.00	99.73	6.00	38.00	26832.00	
	Funding/Backer	4766	160.53	0.00	5.00	67.18	30.70	69.61	6000.00	
	Austrian Location	4766	0.33	0.00	0.00	0.13	0.00	0.00	1.00	
	Platform (1=SN)	4766	0.00	2.00	2.00	2.00	2.00	2.00	2.00	
	Funding Goal (ln)	4766	1.79	0.00	7.94	8.99	9.21	10.13	18.42	
	Funding (ln)	4766	3.53	0.00	2.30	5.12	5.53	7.92	14.98	
	Overfunding (ln)	1046	2.59	0.00	5.32	7.14	7.09	8.81	14.96	
	Backers (ln)	4766	2.03	0.00	0.00	2.17	1.79	3.64	10.20	
	Funding/Backer (ln)	4766	1.86	0.00	1.61	2.94	3.42	4.24	8.70	
	Variables	**N**	**sd**	**min**	**p25**	**mean**	**p50**	**p75**	**max**	**WRST**
Total	Successful	10512	0.49	0.00	0.00	0.40	0.00	1.00	1.00	0
	Funding Goal	10514	993541.60	1.00	2500.00	35043.88	6000.00	15000.00	100000000.00	0
	Funding	10514	43799.27	0.00	84.00	7192.26	1040.00	4898.00	3198516.00	0
	Overfunding	4125	61157.65	1.00	135.00	7597.97	480.00	1684.00	3148516.00	0
	Duration	10514	16.77	1.00	30.00	39.90	34.00	47.00	184.00	0
	Backers	10514	429.18	0.00	3.00	84.42	17.00	62.00	26832.00	0
	Funding/Backer	10514	189.45	0.00	20.49	76.40	45.42	83.33	11952.50	0
	Austrian Location	10514	0.30	0.00	0.00	0.10	0.00	0.00	1.00	0
	Platform (1=SN)	10514	0.50	1.00	1.00	1.45	1.00	2.00	2.00	
	Funding Goal (ln)	10514	1.52	0.00	7.82	8.72	8.70	9.62	18.42	0
	Funding (ln)	10514	3.12	0.00	4.43	6.15	6.95	8.50	14.98	0
	Overfunding (ln)	4125	2.12	0.00	4.91	6.22	6.17	7.43	14.96	0
	Backers (ln)	10514	1.89	0.00	1.10	2.70	2.83	4.13	10.20	0
	Funding/Backer (ln)	10514	1.60	0.00	3.02	3.45	3.82	4.42	9.39	0

Note: This table shows the summary statistics for all variables referred to in the study which are defined following the cited literature. First, descriptive statistics are shown for characteristics of campaigns from the Startnext.com (SN) platform, before those for the Kickstarter.com (KS) are shown. Finally, a table with the total for all projects stemming from both platforms follows. All amounts are translated into EUR values. The last column in the third table reports the results, i.e. p-values, for Wilcoxon-rank-sum-tests performed for several independent project characteristics common for projects stemming from both platforms. The analysed project characteristics are funding goal (in €), funding (in €), overfunding (in €), campaign duration (in days), number of backers, funding per backer and Austrian location, platform (1=SN, 2=KS), and the aforementioned variables, for which the natural logarithm was determined for regression analysis.

Summing up, 40.46% (4,253) of the launched projects are successful. From the 10,514 projects, 5,747 and 4,765 campaigns were initiated on the platform Startnext (1) and Kickstarter (2), respectively. Surprisingly, on Startnext (1) 3,182 equaling 55.4% of 5,747 projects launched between 2015 and 2017 at least reached their funding goal, while on Kickstarter (2) there were 1,071 out of 4,765 successful campaigns, which is only 22.5%. Out of the 10,512 campaigns 9,453 are initiated in Germany and 1,059 in Austria which reflects the fact that Germany is 10 times as big as Austria. As indicated in Table 3 by the p-values from Wilcoxon-Rank-Sum-Tests (WRST), we see that all variables differ across the two platforms when compared; a fact often overseen in crowdfunding research where data from many platforms are regularly added.

We observe positive overfunding amounts for 4,125 out of 10,512 projects (1,046 on Startnext (SN) and 3,079 on Kickstarter (KS)), while 6259 projects show no overfunding as they are underfunded. Another 130 projects exactly reach the required funding goal, thus overfunding equals zero in these cases. The amount of overfunding varies to a high degree, which is reflected by the upward skewed mean of 23,866 EUR driven by a maximum of 3,148,516 EUR on KS gained by a teeth brush project versus the upward skewed mean of 2,071 EUR by a maximum of 417,359 EUR on SN earned for a higher education refugee project. For regression analysis, logarithmic values will be used as they are closer to the median, which in crowdfunding samples is most representative of standard projects. Crowdfunding sample means and medians often differ a lot – this, however, is seldom recognized in relevant research.

It is also important to differentiate between output and input variables because the latter are all 100% controlled for and decided by the project initiator ex-ante compared to the variables reflecting the campaign outcomes. Output variables like the number of backers, funding received, and number of comments/updates are all dependent on the input variables like funding goal, duration of the project, number of pictures, and the inclusion of a video set ex-ante. The mixing of input with output variables is a common mistake in crowdfunding research. For example, the number of backers is often used as an input variable, even though this is an ex-post-developed measure.

5. Data Analysis

5.1 Univariate Analysis and Summary Statistics

Table 4: Full Sample Pearson Rank Sum Correlations

Pearson Corr.	Success_dv	Overfunding	Funding_goal	Duration	Platform	Backers	Funding_PerB	Austrian_loc
Success_dv	1							
	10512							
Overfunding	.	1						
	.							
	4125	4125						
Funding_goal	-0.0221	0.2500*	1					
	0.0235	0						
	10512	4125	10514					
Duration	0.0550*	-0.0214	0.0157	1				
	0	0.1695	0.1075					
	10512	4125	10514	10514				
Platform	-0.3336*	0.1551*	0.0273*	-0.2903*	1			
	0	0	0.0052	0				
	10512	4125	10514	10514	10514			
Backers	0.1911*	0.7752*	0.0007	0.0014	0.0325*	1		
	0	0	0.9414	0.885	0.0009			
	10512	4125	10514	10514	10514	10514		
Funding_Pe~r	0.0956*	0.1371*	-0.0006	0.0469*	-0.0443*	0.0091	1	
	0	0	0.9527	0	0	0.349		
	10512	4125	10514	10514	10514	10514	10514	
Austrian_l~v	-0.0439*	0.0525*	-0.0028	-0.0263*	0.0736*	0.0025	0.0520*	1
	0	0.0007	0.7777	0.007	0	0.7964	0	
	10512	4125	10514	10514	10514	10514	10514	10514

*Note: This table reports Pearson rank sum correlation coefficients for several project characteristics, p-values and numbers of observations, while * indicates significance at the 1% level. Success is reflected by the dummy variable success_dv and the occurrence of overfunding. The analysed project characteristics are funding goal (in €), campaign duration (in days), number of backers, funding per backer and Austrian location.*

Table 4 reports Pearson rank sum correlation coefficients, p-values, and numbers of observations, while * indicates significance at the 1% level. As further shown in Table 5, Wilcoxon-Rank-Sum-Tests confirm significant differences regarding the levels of overfunding and between many input variables on both platforms in all clusters. However, no differences between the two platforms seem to exist in the Lifestyle sector concerning the pre-set funding goal, in the Sustainability area regarding the amount of realizable overfunding, and in the case of projects launched in Austria for the aforementioned two industry categories in the period 2015-2017. Table 5, Panels B and C show that the highest median funding goals are observable in the Technology, Lifestyle, and Sustainability cluster where also the highest overfunding amounts are realizable as suggested by the skewed mean funding figures. The highest median funding is raised by Sustainability, Art, and Publishing projects – for these projects larger groups of backers pay the largest amounts of money. The Appendix shows the differences between means and medians of the main variables of interest for individual category clusters. In the Appendix, we observe that in most of the categories, the funding goals set by initiators on the KS platform are higher than on SN leading, most probably, to smaller crowdfunding amounts and failure on this all-or-nothing platform. The supporters may find the pre-set funding goals to be inappropriately high and refrain from investing their money.

Table 5: Results (p-values) of Wilcoxon-Rank-Sum-Tests Applied to Projects from Grouped Industry Categories for the Startnext and Kickstarter Platforms

Panel A/ Industry Cluster	**Art**	**Technology**	**Sustainability**	**Publishing**	**Lifestyle**
		WRST (p-values)			
Successful	0	0	0	0	0
Funding Goal in EUR	0	0	0	0	0.3998
Funding in EUR	0	0	0	0	0
Overfunding in EUR	0	0	0.1564	0.0007	0
Duration in days	0	0	0	0	0
Backers	0	0	0	0	0
Funding per Backer	0	0	0	0	0
Austrian Location	0	0.0001	0.6725	0.0410	0.2980
Panel B / Industry Cluster	**Art**	**Technology**	**Sustainability**	**Publishing**	**Lifestyle**
		Mean			
Funding Goal in EUR	34340.10	51781.06	16999.19	22163.83	38177.35
Funding in EUR	6307.36	11696.04	7742.45	3131.17	7707.92
Overfunding in EUR	5527.59	25003.61	4096.86	2105.12	10525.67
Duration in days	39.58	39.96	44.99	40.52	37.66
Backers	72.35	79.09	102.77	61.25	134.89
Funding per Backer	77.36	106.35	93.98	45.26	51.87
Austrian Location	0.10	0.11	0.11	0.10	0.11
Panel C / Industry Cluster	**Art**	**Technology**	**Sustainability**	**Publishing**	**Lifestyle**
		Median			
Funding Goal in EUR	5000	10000	8500	4500	10000
Funding in EUR	1393	543	1595	602	558
Overfunding in EUR	370	839	873	337	1024
Duration in days	34	34	42	35	31
Backers	22	9	25	14	13
Funding per Backer	50	45	51	33	35

Note: This table reports the results, i.e. p-values, for Wilcoxon-rank-sum-tests performed for several independent project characteristics common for projects stemming from both platforms in Panel A. The analyzed project characteristics are funding goal (in €), funding (in €), overfunding (in €), campaign duration (in days), number of backers, funding per backer and Austrian location. Panel B and C show the mean and median values, respectively, for the aforementioned variables for both platforms in total for the industry clusters Art, Technology, Sustainability, Publishing and Lifestyle. The Appendix provides more details.

5.2 Multivariate Analysis of Funding and Overfunding Dynamics in Crowdfunding

In the following, OLS regressions of various project characteristics on the level of project funding and Logit and Probit regressions of those on success probability are performed to gain more precise insights into the underlying dynamics.

5.2.1 The Drivers Helping to Reach Higher Funding

Table 6 reports the results of OLS regressions of various project characteristics on the level of project funding (ln_Funding). As compared to columns (1)-(4), columns (5)-(6) separately focus on the SN and KS project campaigns.

Table 6: Determinants Affecting Raised Funding Amounts (Ln_Funding)

Variable Data	T4_c1 All	T4_c2 All	T4_c3 All	T4_c4 All	T4_c5 Startnext	T4_c6 Kickstarter
Dep. Variable	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding
Funding Goal (ln)	0.2866***	0.2278***	0.2495***	0.2224***	0.4632***	0.2224***
Duration	0.0012	-0.0160***	-0.0159***	-0.0156***	0.0056***	-0.0156***
Austrian Location	-0.071	-0.0739	-0.0825	-0.0824	-0.0346	-0.0824
Startnext_SN_dv	2.0207***	-0.3645	-0.4959	0.0716		
Funding Goal (ln)*SN_dv		0.1850***	0.1958***	0.2407***		
Duration*SN_dv		0.0215***	0.0218***	0.0212***		
Austrian Location*SN__dv		0.0317	0.0634	0.0478		
Art_cluster_dv			0.7176***	1.3482***	0.1683*	1.3482***
Technology_cluster_dv			0.0975	0.9793***	-0.7974***	0.9793***
Sustainability_cluster_dv			0.2528*	(omitted)	-0.1603	(omitted)
Publishing_cluster_dv			(omitted)	-0.0607	(omitted)	-0.0607
Lifestyle_cluster_dv			0.3504***	0.9336***	-0.1699	0.9336***
Art_cluster*SN_dv				-1.0196***		
Technology_cluster*SN_dv				-1.6164***		
Sustainability_cluster*SN_dv				(omitted)		
Publishing_cluster*SN_dv				0.221		
Lifestyle_cluster*SN_dv				-0.9432***		
Constant	2.5080***	3.6325***	2.9983***	2.6477***	2.8796***	2.6477***
N	10514	10514	10514	10514	5748	4766
R2	0.1101	0.1147	0.1227	0.1287	0.0625	0.0295
Adj. R2	0.1097	0.1141	0.1218	0.1274	0.0613	0.0281

*Note: This table reports the results of OLS regressions of various project characteristics on the level of funding (Ln_funding) collected in a crowdfunding campaign for the 10,514 sample projects excluding and including interaction terms consisting of platform choice between Startnext and Kickstarter represented by the dummy variable SN_dv (becoming 1 for Startnext and 0 for Kickstarter) and industry category dummy variables (the omitted category – baseline – is Sustainability in column (4), (6) and Publishing in column (5)). These interactions, along with all project characteristics, are regressed on the funding amount. Standard errors are robust and *, **, *** indicate significance at the 10, 5, and 1% level, respectively.*

Columns (4)-(6) show that, even though we have more projects from Startnext.com than from Kickstarter.com, projects from KS dominate the results for the whole sample of 10,514 observations. Thus, it is essential to distinguish between different platforms to gain representative results. Furthermore, there are some common patterns observable. In Table 6, column 4 we face the problem of heteroscedasticity according to White's test with a p-value=0.000, (not reported) where the hypothesis of homogenous residuals is rejected. In order to avoid arising problems we use for all OLS regressions that follow White's robust standard errors in STATA as they are variations of Table 6, column 4. We also perform a link test for the misspecification of the model and find no indication of misspecification as the hatsq p-value=0.107 (not reported).

The higher the funding goal, the higher the final funding amount on both platforms, however, a 1% change in the funding goal amount increases the funding on KS only by 0.22%, while on SN more than double this amount with 0.46%. This stands in contrast to most of the previously performed studies, e.g. Frydrych et al. (2014), Patel and Devaraj (2016), and Barbi and Bigelli (2017). Hence, the choices of particular samples (sample size, period, country/region, platform choice) or/and U-shaped or other non-linear relationships might be the driving forces behind most results. One must consider that sometimes founders are allowed to do self pledges up to 1.6% on SN (Corsetto and Regner (2018, 2021)) and that the funding goal should be in a range, which is typical for a particular industry (Galkiewicz and Galkiewicz (2018)). The longer the duration, the higher the final funding amount on SN and lower on KS – the mixed results confirm contrasting findings from literature (e.g. Frydrych et al. (2014) and Cordova et al. (2015)), which might be the outcomes of nonlinear relationships, e.g. U-shape. However, the impact of duration is only statistically significant, while its economic relevance is negligible on both platforms. On SN, projects from the Technology cluster get significantly less funding as compared to those from the Publishing area. On KS, projects from the clusters: Art, Technology, and Lifestyle get significantly more financing than those from the Sustainability field. These differences imply that different groups of initiators and investors visit various platforms and invest in specific projects.

Strausz (2017) suggests that the higher the uncertainty about the market size, the larger the difference between funding and funding goal may be, hence resulting in over- or underfunding. The latter is also increased if potential supporters become doubtful about the project or the founder's quality. For example, the funding goal may seem to be inappropriately high for project realization. We also think that backers in donation- and reward-based crowdfunding are less professional with their altruistic and hedonistic (Gierczak et al. (2016)) motivations than those engaged in crowdlending or equityinvesting focusing on profiting. This might further increase the level of over- or underfunding across different platforms and industries. The next analysis provides a more differentiated picture of the impact of project characteristics on funding levels in various industries on both platforms.

Funding Success Drivers Identifiable in Various Industries on Different Platforms. As shown by Table 7, a funding goal increase of 1% significantly increases the final funding amount in the Art cluster by an economically relatively low 0.55% on SN and 0.35% on KS. The regressions in Table 7a focus on SN's sample projects, while KS's projects are utilized in Table 7b. In the Technology cluster, projects get on both platforms 0.21% more of funding with a 1% increase in the funding goal. However, only on SN, a 1% higher funding goal amount increases significantly the funding of projects from the Sustainability and Publishing cluster by 0.38% and 0.64%, respectively. A 10-day longer duration significantly (in statistical terms only) increases the funding of projects from the field of Art by 0.05% and Technology by 0.16% on SN, while on KS in Lifestyle by 0.57%.

Table 7: **The Determinants of Funding (Ln_Funding) in Various Industry Clusters on Two Platforms**

Table 7a

Variable	**T5a_c1**	**T5a_c2**	**T5a_c3**	**T5a_c4**	**T5a_c5**
Data	**Startnext**	**Startnext**	**Startnext**	**Startnext**	**Startnext**
Dep. Variable	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding
Funding Goal (ln)	0.5495***	0.2124***	0.3830***	0.6358***	0.3504***
Duration	0.0049**	0.0160***	0.0018	-0.001	0.0061
Austrian Location	-0.1327	0.2709	-0.0128	0.0655	0.099
Constant	2.3751***	3.7890***	3.6183***	1.7784**	3.6954***
N	3087	710	786	571	594
R2	0.079	0.0288	0.0299	0.1007	0.028
Adj. R2	0.0781	0.0247	0.0262	0.096	0.023

Table 7b

Variable	**T5b_c1**	**T5b_c2**	**T5b_c3**	**T5b_c4**	**T5b_c5**
Data	**Kickstarter**	**Kickstarter**	**Kickstarter**	**Kickstarter**	**Kickstarter**
Dep. Variable	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding	Ln_Funding
Funding Goal (ln)	0.3479***	0.2123***	-0.1071	-0.0282	0.1509***
Duration	-0.0009	-0.0134	-0.0319	-0.008	-0.0568***
Austrian Location	-0.2168	0.4761	-0.9261	0.2819	-0.467
Constant	2.4077***	3.5729***	5.9556***	4.4361***	5.6443***
N	2231	969	108	456	1002
R2	0.0275	0.0127	0.0335	0.0019	0.0366
Adj. R2	0.0262	0.0097	0.0056	0.0017	0.0337

*Note: This table reports the factors affecting the amount of funding (Ln_Funding) collected in a crowdfunding campaign for various industry cluster samples on two platforms in an OLS setting in. The following industry groups are created for the first time based on project similarities and shown in columns (1) to (5), respectively: (1) Art cluster: Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, Theater, (2) Technology cluster: Education, Technology, Innovation, Technology, (3) Sustainability cluster: Agriculture, Crafts, Community, Environment, Social Business, (4) Publishing cluster: Audio book, Comics, Journalism, Literature, Publishing, and (5) Lifestyle cluster: Food, Games, Sport. The regression in Table 7a focuses on Startnext's sample projects, while Kickstarter's projects are utilized in Table 7b. Standard errors are robust and *,**,*** indicate significance at the 10, 5, and 1% level, respectively.*

We perform an additional robustness test on which factors affect the number of backers as funding is the outcome of backers' financial engagement in a project. Thus, by replacing Ln_Funding with Ln_Backers_No we obtain the following OLS results in Table 8. Even though the analysis provides only a partial picture, it confirms previously obtained findings and reveals interesting patterns. For example, in all clusters, except for Technology, an increase in the funding goal amount attracts more backers on SN. This holds similarly for projects from the clusters Art, Technology, and Lifestyle on KS. In SN's Technology cluster, only a longer duration slightly increases the number of supporters and this is also the case for KS's Sustainability, Publishing, and Lifestyle projects. Finally, projects promoted in Austria attract significantly fewer backers, but those who engage provide higher amounts of money through crowdfunding. In consequence, the final funding amounts remain unaffected by the country of origin as previously presented in Table 7. Overall, our results indicate that different levels of over- or underfunding depend on platform choice and the belonging of projects to a particular industry. The main reason for diverging levels of funding remains the uncertainty about the underlying market size/final demand and project quality as suggested by Strausz (2017).

Table 8: Factors Influencing the Attention of Backers in Various Industry Clusters on Different Platforms

Table 8a

Variable Data	T6a_c1 Startnext	T6a_c2 Startnext	T6a_c3 Startnext	T6a_c4 Startnext	T6a_c5 Startnext
Dep. Variable	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No
Funding Goal (ln)	0.3155***	0.0286	0.2170***	0.3609***	0.2056***
Duration	0.0016	0.0059**	0.0017	-0.0052	0.0022
Austrian Location	-0.2314**	-0.1474	-0.0366	-0.0173	-0.0036
Constant	0.5164**	2.0728***	1.2464**	0.5583	1.3693**
N	3087	710	786	571	594
R2	0.057	0.0069	0.0204	0.063	0.0181
Adj. R2	0.0561	0.0027	0.0166	0.058	0.0131

Table 8b

Variable Data	T6b_c1 Kickstarter	T6b_c2 Kickstarter	T6b_c3 Kickstarter	T6b_c4 Kickstarter	T6b_c5 Kickstarter
Dep. Variable	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No	Ln_Backers_No
Funding Goal (ln)		0.0865**	-0.1248	-0.0049	0.0794**
Duration	0.0008	-0.0088*	-0.0226*	-0.0146**	-0.0363***
Austrian Location	-0.2465**	0.1002	-0.8629**	0.0812	-0.4630**
Constant	0.7500***	1.5589***	3.3937***	2.2138***	2.8764***
N	2231	969	108	456	1002
R2	0.023	0.0071	0.0908	0.0093	0.0383
Adj. R2	0.0217	0.004	0.0646	0.0027	0.0354

*Note: This table reports the factors affecting the number of backers (Ln_Backers_No) providing money in a crowdfunding campaign for various industry cluster samples on two platforms in an OLS setting. The following industry groups are created for the first time based on project similarities and shown in columns (1) to (5), respectively: (1) Art cluster: Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, Theater, (2) Technology cluster: Education, Technology, Innovation, Technology, (3) Sustainability cluster: Agriculture, Crafts, Community, Environment, Social Business, (4) Publishing cluster: Audio book, Comics, Journalism, Literature, Publishing, and (5) Lifestyle cluster: Food, Games, Sport. The regression in Table 8a focuses on Startnext's sample projects, while Kickstarter's projects are utilized in Table 8b. Standard errors are robust and *,**,*** indicate significance at the 10, 5, and 1% level, respectively.*

5.2.2 The Determinants of Success

Table 9 and Table 10 report the marginal probabilities of logit and probit regressions, respectively, for reaching funding as high as the funding goal, i.e. success with the dummy variable success_dv becoming 1, evaluating all independent variables at their means which are provided in Table 3 or Table 5 and dummy variables when switching from 0 to 1.

Table 9: The Drivers of Success Determined via Logit Regressions (Success_dv)

Variable	T4_c1	T4_c2	T4_c3	T4_c4	T4_c5	T4_c6
Data	All	All	All	All	Startnext	Kickstarter
Dependent variable	success_dv	success_dv	success_dv	success_dv	success_dv	success_dv
Funding Goal (ln)	-0.0715***	-0.0565***	-0.0523***	-0.0544***	-0.0939***	-0.0448***
Duration	-0.0002	-0.0018***	-0.0019***	-0.0019***	0.0004	-0.0015***
Austrian Location	-0.0183	-0.0319	-0.0344	-0.0339	-0.0065	-0.0279
Startnext_SN_dv	0.2832***	0.4973***	0.4540***	0.4255***		
Funding Goal (ln)*SN_dv		-0.0345***	-0.0311***	-0.0275***		
Duration*SN_dv		0.0021***	0.0022***	0.0022***		
Austrian Location*SN__dv		0.0243	0.0294	0.0282		
Art_cluster_dv			0.0877***	0.0873***	0.1009***	0.0719***
Technology_cluster_dv			-0.0339**	0.0058	-0.0705***	0.0048
Sustainability_cluster_dv			0.0323*	0.0083	0.0388	0.0068
Publishing_cluster_dv			0.0059	-0.0454	0.037	-0.0374
Lifestyle_cluster_dv			(omitted)	(omitted)	(omitted)	(omitted)
Art_cluster*SN_dv				0.0007		
Technology_cluster*SN_dv				-0.0673**		
Sustainability_cluster*SN_dv				0.0256		
Publishing_cluster*SN_dv				0.0777**		
Lifestyle_cluster*SN_dv				(omitted)		
N	10512	10512	10512	10512	5747	4765
R2 (pseudo)	0.1239	0.1263	0.1345	0.1355	0.0564	0.053

*Note: This table reports the marginal probabilities of logit regressions for reaching funding as high as the funding goal, i.e. success with the dummy variable success_dv becoming 1 (or remaining 0 otherwise), evaluating all independent variables at their means which are provided in **Table 3** or the **Appendix** and dummy variables when switching from 0 to 1. Standard errors are clustered at the industry category level and *,**,*** indicate significance at the 10, 5, and 1% level, respectively.*

Columns (1)-(3) show that after the inclusion of additional project characteristics, the explanatory power of the model increases, as indicated by the reported pseudo-R-squared figures. Thus, we consider these variables in all specifications that follow. In the specification containing the extended set of variables in column (4) of Table 9, the probability of a campaign reaching success is significantly negatively affected by a higher funding goal amount, longer duration, and choosing the KS platform for the launch.

Columns 5 to 6 of Table 9 show individual results for the SN and KS platforms, respectively. If ln Funding_goal increases by 1 (from mean 8.72 equalling 6124 EUR to 9.72 equalling 16647 EUR), the success probability decreases by 9.4% on SN and 4.5% on KS. This is in line with the crowdfunding literature, e.g. Crosetto and Regner (2014), Frydrych et al. (2014), Cordova and Gianfrate (2015), Patel and Devaraj (2016) and Barbie and Bigelli (2017) and Forbes and Schaefer (2017). It further indicates that founders get more punished on the SN than on the KS platform for pre-setting the funding goal too high. Moreover, 10 days increase in duration as compared to the mean of 40 days, decreases the success probability on KS only by a negligible 1.5%. Launching projects from the broader Art category (Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, and Theater) increases the success probability as compared to the Lifestyle cluster by 7.2% on KS and 10.1% on SN. In contrast, initiating projects from the Technology cluster decreases the success probability as compared to the Lifestyle cluster by 7.1% on SN – in Table 6 it was previously shown that Startnext's Technology cluster projects get significantly less funding. Patterns observable from unreported Probit regressions are qualitatively and quantitatively comparable to those observed from Logit regressions. In sum, these findings confirm that the choice of a particular platform affects a crowdfunding project's chances for success.

In additional tests considering the Heckman correction (Heckman (1976, 1979)) based on maximum likelihood estimation for non-random self-selection of campaigns into specific platforms we also obtain interesting results. For instance, having an ex-ante Art project in place significantly increases the probability to use the SN platform and positively affects the success probability as shown in column 4 of Table 10. In contrast, while a Technology project increases the probability to use the SN platform, having this type of project decreases the chances for success. The findings in columns 1 and 4 confirm that a higher funding goal decreases the chances for success. This is comparable to previously obtained results. Column 5 shows that an overfunding amount higher than 150% of the funding goal can be obtained if projects from the Sustainability area are launched. Finally, column 6 of Table 10 shows that the general level of overfunding (represented by Ln_Overfunding) is significantly positively affected by a longer duration and negatively by projects from the Art, Technology, or Publishing category. Thus, an industry category of a project and the platform choice matter.

Table 10: The Relevance of Platform Choice for Success and Higher Amounts of Funding

	T8_c1	T8_c2	T8_c3	T8_c4	T8_c5	T8_c6
Dep. variable 1st stage	Startnext_dv	Startnext_dv	Startnext_dv	Startnext_dv	Startnext_dv	Startnext_dv
Art_cluster_dv	0.5292***	0.5286***	0.7057***	0.5292***	0.5286***	0.7057***
Technology_cluster_dv	0.1315***	0.1315***	0.0389	0.1315***	0.1315***	0.0389
Sustainability_cluster_dv	1.4964***	1.4971***	1.5710***	1.4964***	1.4971***	1.5710***
Publishing_cluster_dv	0.4669***	0.4669***	0.6047***	0.4669***	0.4669***	0.6047***
Liefestyle_cluster_dv	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
_cons	-0.3261***	-0.3261***	-0.8203***	-0.3261***	-0.3261***	-0.8203***
mills lambda	-0.1082***	-0.0574***	-0.1937	0	0	0
Dep. variable 2nd stage	**Success_dv**	**High_Overfun_dv**	**ln_Overfunding**	**Success_dv**	**High_Overfun_dv**	**ln_Overfunding**
Funding Goal (ln)	-0.1034***	-0.0348***		-0.0925***	-0.0312	
Duration	0.0003	0	0.0111***	0.0004	0	0.0101***
Austrian Location	-0.0105	-0.0007	0.1387	-0.006	-0.0028	0.0485
Art_cluster_dv				0.1075***	-0.0215*	-0.8844***
Technology_cluster_dv				-0.0692***	-0.0074	-0.6109***
Sustainability_cluster_dv				0.0403	0.0422***	0.0842
Publishing_cluster_dv				0.0432	0.0013	-0.8250***
Liefestyle_cluster_dv				(omitted)	(omitted)	(omitted)
_cons	1.4924***	0.3804***	5.5947***	1.2649***	0.3794***	6.1340***
N	10513	10511	7845	10513	10511	7845
R2	0.0542	0.0542	0.0693	0.0542	0.0542	0.0693
Wald test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: This table reports the results for the relevance of various project characteristics for reaching the funding goal or/and high amounts of (over-)funding. For the latter the "success_dv" is replaced the dummy variable "high_overfun_dv" and by the variable "Ln_Overfunding" equal to [Ln(Funding – Funding goal)]. However, for the high overfunding dummy variable the threshold is chosen randomly. It is defined as obtained funding equal to or higher than 150% of the funding goal (i.e.

high_overfun_dv = 1). The analyses performed in this table are extended by applying the Heckman correction (Heckman (1976, 1979)) based on maximum likelihood estimation for non-random self-selection of campaigns into specific platform. For the latter the inverse of the Mill's ratio and the p-value of the Wald test are also reported; the results from the selection equation are shown in the upper part of the table. In the selection regression (first stage) the focus lies on the impact of industry categories on a founder's general decision to choose a platform like Startnext versus Kickstarter (represented by Startnext_dv). In the bottom part of Table 9 the remaining impact of project characteristics on the extent of funding, i.e. for reaching the funding goal/success, increasing overfunding or gaining higher overfunding (second stage) is shown. The following industry groups are considered: (1) ***Art*** *cluster: Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, Theater, (2)* ***Technology*** *cluster: Education, Technology, Innovation, Technology, (3)* ***Sustainability*** *cluster: Agriculture, Crafts, Community, Environment, Social Business, (4)* ***Publishing*** *cluster: Audio book, Comics, Journalism, Literature, Publishing, and (5)* ***Lifestyle*** *cluster: Food, Games, Sport. *,**,*** indicate significance at the 10, 5, and 1% level.*

6. Conclusions

This study provides unique results on factors relevant to the success of crowdfunding campaigns run in Europe between 2015 and 2017 on the platforms Kickstarter.com and Startnext.com. Our goal is to offer practical guidance to founders about general and industry-specific dynamics on which platform to choose for their projects to reach the highest funding.

In the main analyses, significant differences between the drivers of success depending on platform choice or whether launched projects belong ex-ante to a particular industry category are identified. It is documented that an increase in the project's funding goal from ca. 6000 EUR to ca. 16000 EUR results in a lower probability of a campaign's success, defined as reaching the funding goal, i.e. decreases it by 9% on Startnext and 4.5% on Kickstarter. On Startnext, projects from the Technology cluster get less funding than those from the Publishing counterpart, while on Kickstarter, projects from Art, Technology, or Lifestyle field reach higher financing as compared to the Sustainability area. Finally, launching a project from the broader Art category, instead of Lifestyle, has a 10.1% and 7.2% higher chance of success on Startnext and Kickstarter, respectively. The diverging drivers of success documented for projects launched in Germany are equally important for projects initiated in Austria. The aforementioned comparisons reveal significant differences between groups of initiators and investors visiting various platforms and industry clusters which might be potentially interesting for founders, funders, and its advisors.

We add to the growing body of literature on drivers of success determining the level of funding originating from Frydrych et al. (2014), Mollick (2014), and Koch (2016) by showing how the sample choice (size, period, industry, region/country, platform) leads to diverging results in the literature. Future research should focus on larger samples of successful and unsuccessful projects stemming from various platforms and covering different industry clusters to identify more precisely – and universally representative – patterns.

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Appendix: Startnext and Kickstarter Projects – Differences Between Means and Medians of the Main Variables of Interest for Individual Categories

Industry Cluster	Art		Technology		Sustainability		Publishing		Lifestyle	
Platform	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter
					Mean					
Funding Goal in EUR	7127	71995	14640	78995	18012	9626	5747	42721	16537	51006
Funding in EUR	4526	8773	5338	16355	8626	1311	3614	2526	8315	7348
Overfunding in EUR	1346	18477	3902	62104	4261	1677	1368	5195	3126	20598
Duration (days)	43	34	46	36	46	34	45	35	45	33
Backers (number)	60	90	51	99	114	23	71	50	103	154
Industry Cluster	**Art**		**Technology**		**Sustainability**		**Publishing**		**Lifestyle**	
Platform	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter	Startnext	Kickstarter
					Median					
Funding Goal in EUR	4000	7000	6783	20000	9700	3250	3500	5500	10000	10000
Funding in EUR	2160	465	1134	251	2359	70.5	1683	46.5	2334	182
Overfunding in EUR	310	745	337	4345	891	569	314	680	775	2692
Duration (days)	39	30	42	30	42	30	41	30	42	30
Backers (number)	31	9	14.5	5	30	3	33	2.5	33	6

Note: This table reports the means and medians of individual project characteristics of 10 514 Startnext.com and Kickstarter.com campaigns launched between 2015 and 2017 belonging to specific industry categories. The means of the variables are relevant for the interpretation of the marginal probabilities from Logit and Probit regressions reported in Tables 7-8. The following industry groups are created for the first time based on project similarities and shown in columns (1) to (5), respectively: (1) ***Art*** *cluster: Art, Dance, Design, Event, Fashion, Film & Video, Music, Photography, Theater, (2)* ***Technology*** *cluster: Education, Technology, Innovation, Technology, (3)* ***Sustainability*** *cluster: Agriculture, Crafts, Community, Environment, Social Business, (4)* ***Publishing*** *cluster: Audiobook, Comics, Journalism, Literature, Publishing, and (5)* ***Lifestyle*** *cluster: Food, Games, Sport.*

APPLIED FINANCE LETTERS

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UNCERTAINTY AND RISK IN CRYPTOCURRENCY MARKETS: EVIDENCE OF TIME-FREQUENCY CONNECTEDNESS

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Abstract

This study aims to investigate the spillover effects from geopolitical risks (proxied by the geopolitical risk index) and cryptocurrencies-related uncertainty (proxied by the Cryptocurrency Uncertainty Index) to cryptocurrencies. We utilise the Baruník and Křehlík (2018) framework to detect time-frequency connectedness. Our investigation for the period 2017 to 2022 discovers significant spillover effects from both indices to cryptocurrencies. Utilising the information transmission theory and network graphs, our findings reveal that some cryptocurrencies function as net receivers of spillovers from geopolitical risks and uncertainty in the short-term, while over longer time horizons they transform into net transmitters of spillovers to uncertainty. The study contributes to better understanding how uncertainty due to various factors (geopolitical, policy changes, regulatory changes, etc.) could affect the cryptocurrencies' markets.

Keywords: cryptocurrencies; geopolitical risk; market uncertainty; time–frequency connectedness

1. Introduction

Cryptocurrencies have undergone a dramatic transformation in recent years. Currently, the cryptocurrency market has a total capitalisation of approximately US$ 0.948 trillion. However, Bitcoin (BTC) alone had a market capitalisation of US$ 1.28 trillion in November 2021, despite experiencing many bubbles and crashes throughout its history (Thampanya et al., 2020). Bitcoin experienced a dramatic surge from US$ 1,000 to nearly US$ 20,000 in late 2017, plummeting back down to US$ 3,000 in 2019. Regulatory crackdowns have had a notable impact on cryptocurrencies' value in many countries, especially China. In 2015, Ethereum (ETH) enabled blockchain technology in smart contracts and sparked the Initial Coin Offer (ICO) boom. More recently, the rise of decentralised finance (DeFi) and decentralised exchanges (DEX) have reshaped the cryptocurrency landscape. Cryptocurrencies now exhibit similar characteristics to those of developed financial markets, such as currency markets (Drożdż et al., 2018).

Recent research has examined the safe haven properties of cryptocurrencies, particularly during the COVID-19 pandemic (Dasauki & Kwarbai, 2021; Kakinuma, 2023; Maitra et al., 2022). Several studies provide evidence that Bitcoin displays safe haven properties comparable to those of gold (Bouri et al., 2020; Shahzad et al., 2019, 2020; Thampanya et al., 2020). In contrast, other studies have found that cryptocurrency markets are highly correlated with equity markets during market downturns (Yarovaya et al., 2022). Thus, the role of cryptocurrencies as a hedge for financial investments remains a topic of hot debate, with uncertainty surrounding their effectiveness.

Our research is grounded in information transmission theory, which emphasises the importance of information in shaping the expectations of investors, traders, and policymakers and influencing the supply and demand equilibrium. In today's digital age, investors have access to a wide range of information channels, including social media, online blogs, and internet news, that can rapidly disseminate information and affect their beliefs and trading decisions. Models based on rational disagreements, such as those developed by He and Wang (1995) and Tetlock (2010), suggest that public information can lead to trade only when it helps resolve information asymmetry and results in traders' beliefs converging (Tetlock, 2014). These models provide a helpful theoretical framework for understanding how the transmission of information can impact financial markets and serve as a basis for our investigation into the relationship between information transmission and market outcomes.

The efficient functioning of financial markets, which encompasses the determination of prices and asset allocations, relies on the intricate interplay between two fundamental factors: the demand for securities by investors and the willingness of companies to supply these securities. Within the realm of finance, information transmission emerges as a pivotal and central player due to its inherent capacity to shape the expectations held by both investors and managers regarding future developments. It is this very influence that subsequently exerts a profound and far-reaching impact on the delicate equilibrium between supply and demand within these markets. Numerous scholarly endeavours have been dedicated to the exploration of information transmission, with a primary focus on the meticulous examination of stock market dynamics in response to a myriad of corporate events. These events span a wide spectrum, encompassing everything from the disclosure of earnings announcements to the dissemination of analyst forecasts. A noteworthy instance that comes to the fore is the seminal work of Fama et al. (1969), which conducted an event study that meticulously examined the trajectory of stock prices for firms following the public revelation of stock splits.

In the realm of the cryptocurrency market, characterised by its rapid pace and the continuous influx of information, these dynamics are no less relevant. Earlier studies have utilised information transmission as a theoretical basis to comprehend the intricate workings of cryptocurrencies (e.g., Akyildirim et al., 2021; Bação et al., 2018; Ji et al., 2019; Koutmos, 2018). In alignment with this existing body of research, our aim was to delve into the theory of information transmission to gain a deeper understanding of how external factors, such as geopolitical risks and regulatory uncertainties, can exert their influence on the conduct of market participants, including both investors and policymakers. At the core of this discussion lies the recognition that information stands as a fundamental driver of market behaviour within the cryptocurrency space. This encompasses a dual nature of information, encompassing both the public information domain, consisting of news reports, social media posts, and official announcements, and the realm of private information, which may be confidentially held by individual investors and insiders within the market. It is through the transmission of information that profound ripple effects are generated, directly impacting market sentiment, liquidity, and the valuation of cryptocurrency assets.

Geopolitical frictions, tensions, and events such as elections can create fluctuations or uncertainties in political environments, which can significantly impact the prices of financial assets. Balcilar et al. (2018) asserted that geopolitical risk is a crucial determinant of investment decisions, as it can alter business cycles, financial markets, and economic trajectories. The risk emanating from geopolitical tensions causes investors to reassess their portfolios taking into account the stability of government policies. For example, the recent disagreement between USA and China over the disputed island in the South China Sea had a significant indirect impact on business sentiments. Increased geopolitical risks increase asset volatility (Al Mamun et al., 2020). As a result, many studies have employed the geopolitical risk index (GPRD) as a proxy for adverse geopolitical events and associated risks (Caldara & Iacoviello, 2022).

Lucey et al. (2022) introduced a new index, the Cryptocurrency Uncertainty Index (UCRY), which captures two primary types of uncertainty: Cryptocurrency Policy Uncertainty (UCRY Policy) and Cryptocurrency Price Uncertainty (UCRY Price). This index can help assess how policy and regulatory debates influence the returns and volatility of cryptocurrencies. Studies by Al-Shboul et al. (2022), Elsayed et al. (2022), Haq and Bouri (2022) have used the UCRY to understand the dynamic connection with cryptocurrencies, equities, and gold and have established strong evidence of their connectedness.

Our research aims to investigate spillover effects from the GPRD and the UCRY to cryptocurrencies. We utilise network graphs from the frequency connectedness framework developed by Baruník and Křehlík (2018) to accomplish this goal. We aim to answer the following two research questions:

RQ 1: Does the magnitude of spillovers from the UCRY exceed those from the GPRD?

RQ 2: Are there any differences in the magnitude of the spillovers caused by UCRY and GPRD in the short, medium, and long terms?

Prior research has explored the impact of different uncertainties on cryptocurrencies, focusing on individual assets or groups of assets. For instance, Raza et al. (2023) examined the effect of financial regulatory policy uncertainty on a portfolio of six cryptocurrencies using a GARCH-MIDAS framework, finding that higher uncertainty was associated with lower volatility. Khalfaoui et al. (2023) employed a quantile cross-spectral analysis and Google Trends data to investigate the impact of the Russia-Ukraine war on cryptocurrencies. Their research revealed that investors responded to the conflict by demanding liquidity, with a resulting decline in cryptocurrency prices. Al-Shboul et al. (2023) find a negative effect of economic policy uncertainty on the total spillover among all currencies (traditional and cryptocurrencies) at all quantiles. In other words, the higher the uncertainty level, the lower the level of connectedness among currencies Tong et al. (2022) quantified the impact of attention from the search engine (Google Trends) and social media attention (Twitter) and documented bi-directional causality between these attentions and cryptocurrencies. Sawarn and Dash (2023), using a time frequency-based connectedness, concluded that US financial stress transmits uncertainty to cryptocurrencies on a net basis. Long et al. (2022) investigated the cross-sectional impact of geopolitical risk on the returns of 2000 cryptocurrencies, establishing that cryptos with higher geopolitical betas tend to underperform those with the lowest betas. Akyildirim et al. (2021) study the dynamic network connectedness between cryptocurrency returns and investor sentiments and find that information transmission is from cryptocurrency returns towards sentiments.

The remainder of the paper is structured as follows. Section 2 provides a description of the data and the methodology, while section 3 summarises the results and offers insights about the findings. Finally, section 4 concludes with some remarks.

2. Data and methodology

2.1 Data description

We use weekly data for nine major cryptocurrencies (Bitcoin, Ethereum, Basic Attention Token, Bitcoin Cash, Binance Coin, Dogecoin, Litecoin, OmiseGO, and Stellar Lumens) and two uncertainty indices, Geo-political Risk Index (GPDR)[1] and Cryptocurrency Uncertainty Index (UCYR Policy), for the period spanning November 5, 2017 to 25 December 25, 2022. We source the data of cryptocurrencies from the website of coinmarketcap.com and GPRD and UCRY data from their official websites. Table 1 provides more details about the variables and notations used, and Figure 1

[1] Geopolitical risk, as defined by Caldara and Iacoviello (2022), pertains to the potential for, occurrence of, and intensification of adverse events linked to wars, terrorism, and any strains among nations and political entities, which disrupt the peaceful progression of international relations. (https://www.matteoiacoviello.com/gpr.htm)

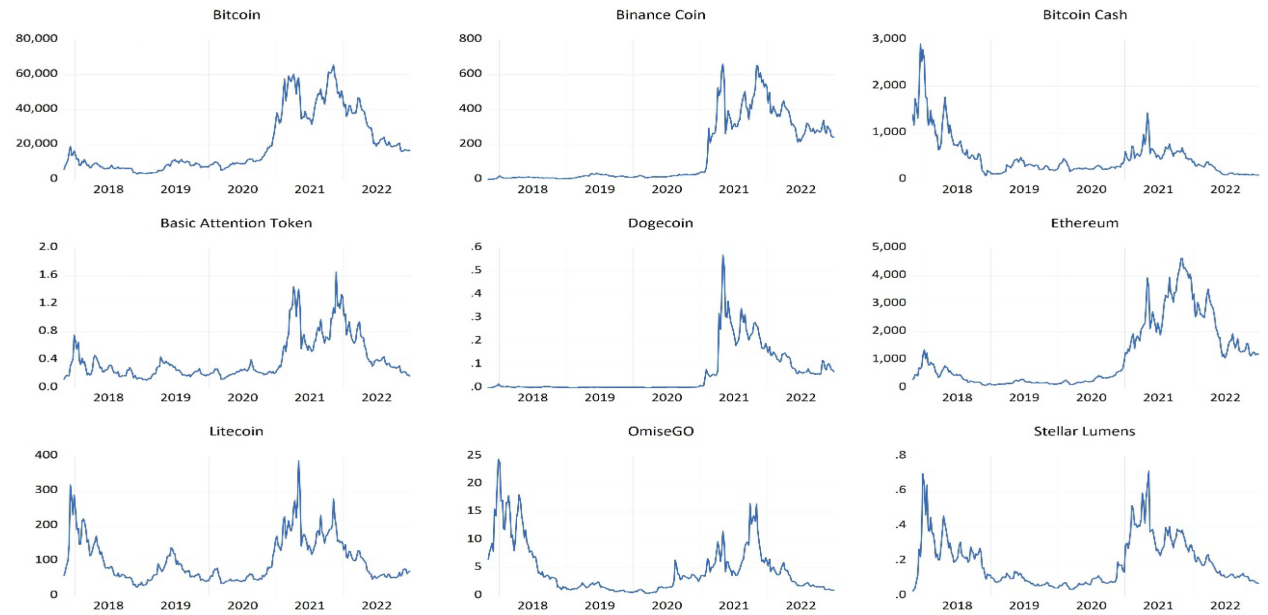
displays the time plots of the nine cryptocurrencies[2]. We calculate weekly percentage change using the formula: $\%\text{Change} = \ln\left({}^{P_t}/_{P_{t-1}}\right)$; where P_t denotes the contemporaneous weekly price while P_(t-1). denotes the previous week's price.

Table 1: Definition of Variables

Variable	Label	Frequency
Geopolitical Risk Index	GPRD	Weekly*
Cryptocurrency Uncertainty Index	UCRY	Weekly
Bitcoin	BTC	Weekly
Ethereum	ETH	Weekly
Basic Attention Token	BAT	Weekly
Bitcoin Cash	BCH	Weekly
Binance Coin	BNB	Weekly
Dogecoin	DOGE	Weekly
Litecoin	LTC	Weekly
OmiseGO	OMG	Weekly
Stellar Lumens	XLM	Weekly

*Note: * GPRD index was converted from daily to weekly frequency by using averages.*

Figure 1: Weekly closing prices of cryptocurrencies



[2] Descriptive statistics for the variables and diagnostic test results are found in the Appendix

2.2 Methodology

Baruník and Křehlík (2018) proposed a frequency connectedness method to measure the directional connectedness between two sets of variables in a frequency domain. Let us denote the two variable sets as X and Y. The frequency connectedness measure is defined as:

$$FC_{X\to Y}(\omega) = \sum_{j=1}^{p_Y} \left| \frac{\sum_{i=1}^{p_X} \gamma_{XY,ij}(\omega)}{\sum_{i=1}^{p_X} \gamma_{XX,ii}(\omega)} \right| \tag{1}$$

Where $\gamma_{XX,ii}(\omega)$ is the auto-covariance of the i-th variable in set X, $\gamma_{XY,ij}(\omega)$ is the cross-covariance between the i-th variable in set X and j-th variable in set Y, and ω is the frequency.

The measure $FC_{X\to Y}(\omega)$ represents the proportion of the variation in set Y that can be explained by setting at frequency ω, after controlling for the variation within set Y at the same frequency. The measure ranges between 0 and 1, where 0 indicates no connectedness, and 1 indicates complete connectedness.

To measure the total frequency connectedness from set X to set Y, the measure is integrated across all frequencies:

$$FC_{X\to Y} = \int_{-\pi}^{\pi} FC_{X\to Y}(\omega) d \tag{2}$$

Similarly, the frequency connectedness from set Y to set X can be defined as:

$$FC_{Y\to X}(\omega) = \sum_{i=1}^{p_X} \left| \frac{\sum_{j=1}^{p_Y} \gamma_{YX,ji}(\omega)}{\sum_{j=1}^{p_Y} \gamma_{YY,jj}(\omega)} \right| \tag{3}$$

And the total frequency connectedness from set Y to set X is derived as:

$$FC_{Y\to X} = \int_{-\pi}^{\pi} FC_{Y\to X}(\omega) d \tag{4}$$

3. Empirical Results

Figure 2 displays the spillovers between GPRD and the selected set of cryptocurrencies.[3] The 1st, 2nd, and 3rd sub-figures (left to right) in figure 2 refer to (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity), respectively. GPRD is a net transmitter of spillovers to DOGE for all three frequency bands, indicating that changes in GPRD are causing spillover effects that are impacting

[3] The corresponding spillovers table can be found in the Appendix.

the price and market dynamics of DOGE. This finding suggests that DOGE is highly sensitive to policy and regulatory risk changes.

Moreover, for frequency 3, BNB, BCH, and ETH are net receivers of spillovers from GPRD, suggesting that changes in GPRD are causing spillover effects impacting these cryptocurrencies' price and market dynamics. The fact that these cryptocurrencies are net receivers of spillovers from GPRD for the long-term frequency band indicates that they may be more sensitive to policy and regulatory risk over a longer time horizon. Overall, these results suggest spillover effects from changes in policy and regulatory risk, as captured by GPRD, to the selected set of cryptocurrencies and that these spillover effects can occur over different time horizons.

Figure 2: GPRD spillover

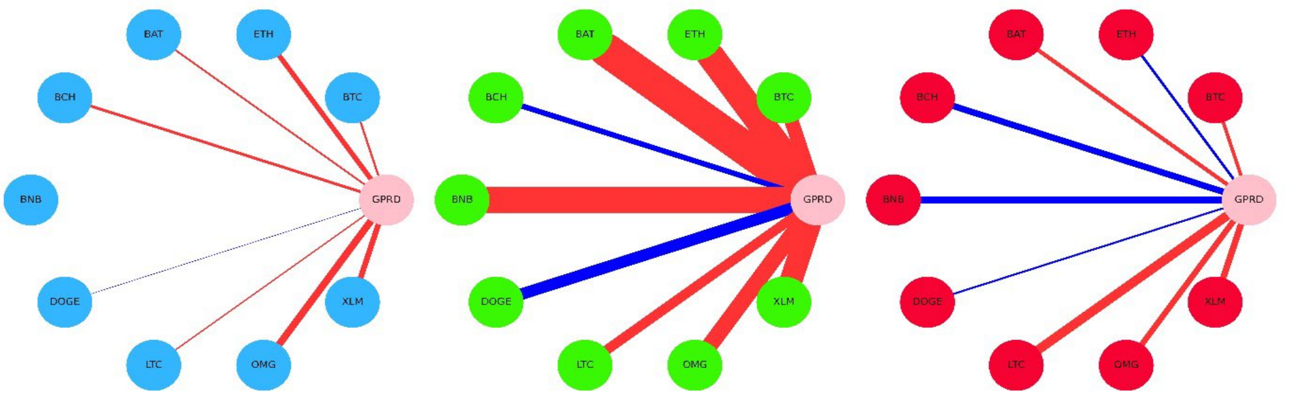
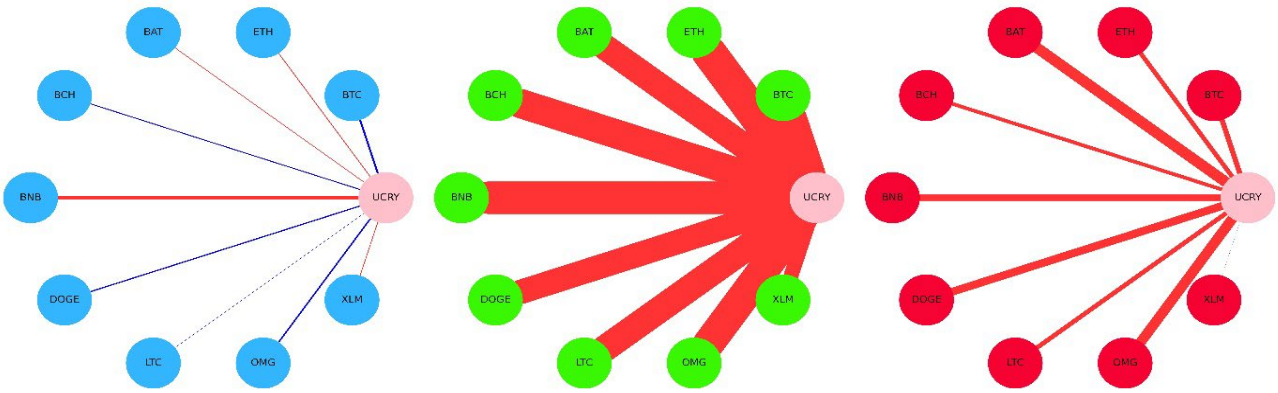


Figure 3 illustrates the spillovers between UCRY and the selected set of cryptocurrencies.[4] The three sub-figures (left to right) show frequency 1 (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity), respectively. For frequency 1, OMG, LTC, DOGE, BCH, and BTC receive net spillovers from UCRY, but none of the cryptocurrencies receive spillovers at frequencies 2 and 3. The results indicate that uncertainty about specific cryptocurrency policies affects the weekly prices of BTC, BCH, DOGE, OMG, and LTC in the short term (frequency 1), as investors react to policy changes by becoming more risk-averse and selling off their holdings. However, this uncertainty does not seem to have a longer term effect (>1 week). Interestingly, these cryptocurrencies become net spillover transmitters over longer horizons to UCRY, suggesting their price and market dynamics impact overall uncertainty in the cryptocurrency market.

[4] The corresponding spillovers table can be found in the Appendix.

Figure 3: UCRY spillover



Figures 4 and 5 provide a visualisation of the total connectedness between GPRD and cryptocurrencies and between UCRY and cryptocurrencies. The results indicate that the magnitude of total connectedness increases as the time horizon extends from short- to medium- to long-term. For the case of GPRD and cryptocurrencies, the total connectedness for frequency 1 (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity) are 68.90%, 72.05%, and 74.98%, respectively. These results suggest that changes in GPRD are highly connected to changes in the selected set of cryptocurrencies and that this connection becomes stronger as the time horizon extends.

Similarly, for the case of UCRY and cryptocurrencies, the total connectedness for frequency 1, frequency 2, and frequency 3 are 69.35%, 70.36%, and 74.65%, respectively. This result suggests that changes in UCRY are also highly connected to changes in the selected set of cryptocurrencies and that this connection becomes stronger as the time horizon extends. These findings highlight the importance of understanding the interconnectedness and spillover effects within the cryptocurrency market and the potential impact of policy and regulatory changes on the overall level of uncertainty in the market. The fact that total connectedness increases with the time horizon suggests that investors and market participants should be mindful of longer-term trends and potential spillover effects when making investment decisions.

It is important to note here that the differing impact of GPRD and UCRY on cryptocurrencies stems from the multifaceted nature of geopolitical risks, the unique attributes of individual cryptocurrencies, the role of market sentiment, and the specific focus of each index. While GPRD casts a wide net over global political events, UCRY delves into the inherent uncertainties specific to the cryptocurrency sector.

Figure 4: Connectedness between GPRD and cryptocurrencies

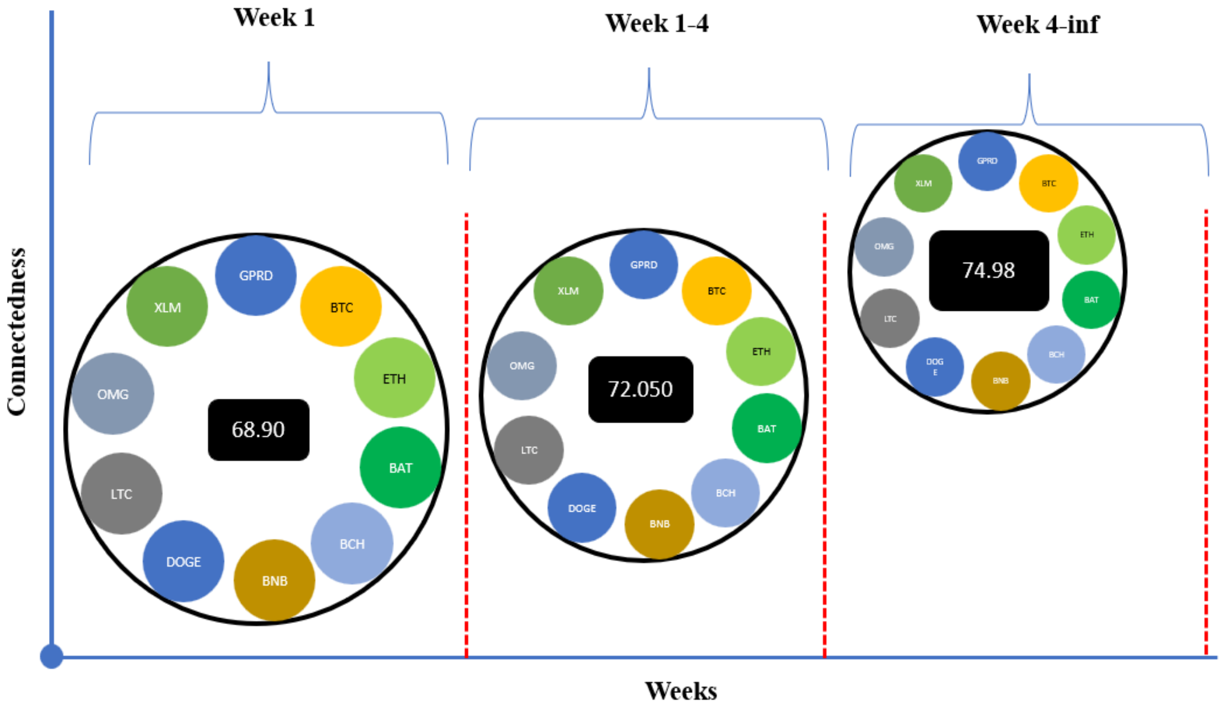
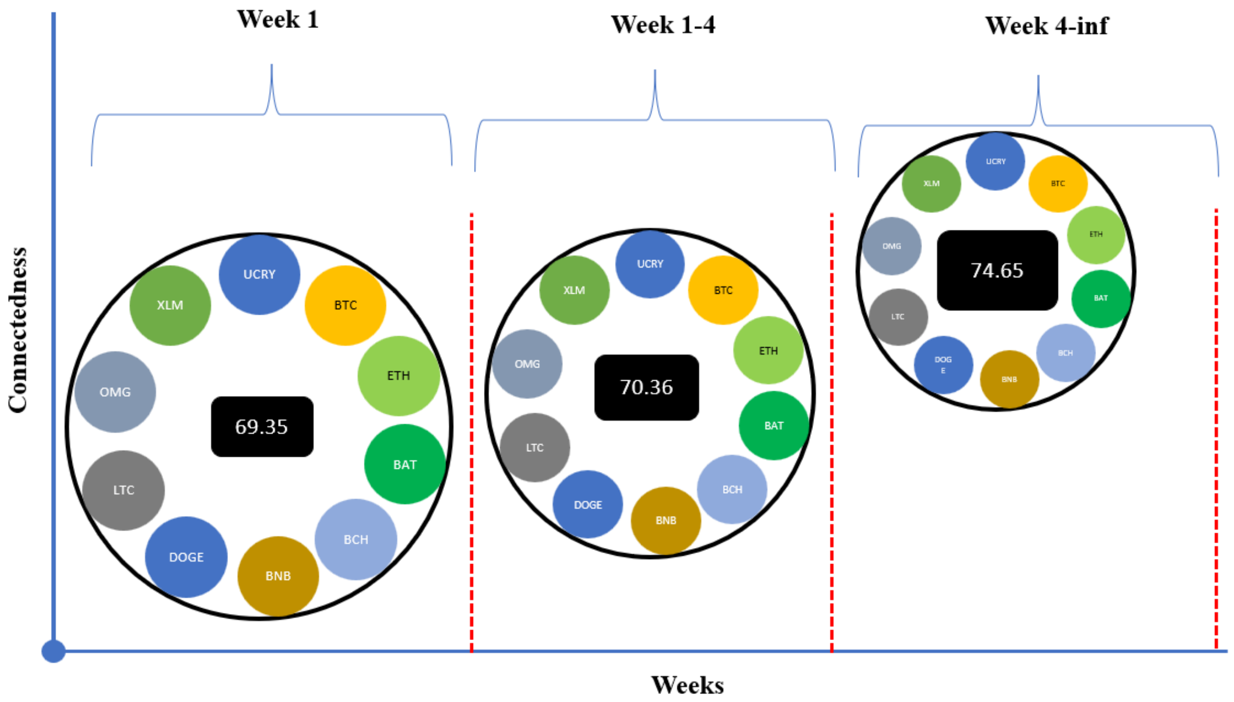


Figure 5: Connectedness between UCRY and cryptocurrencies



4. Concluding Remarks

The present study sheds light on the spillover effects and interconnectedness between geopolitical risk, uncertainty related to cryptocurrencies, and prices of a selected set of major cryptocurrencies: Bitcoin, Ethereum, Basic Attention Token, Bitcoin Cash, Binance Coin, Dogecoin, Litecoin, OmiseGO, and Stellar Lumens.

Our findings indicate that among the nine cryptocurrencies examined, Dogecoin is the most sensitive to policy and regulatory risk changes, as spillover effects from changes in geopolitical risk impact it over all three horizons. Moreover, Binance Coin, Bitcoin Cash, and Ethereum are net receivers of spillovers from geopolitical risk over longer time horizons, indicating their time-dependent sensitivity to policy and regulatory risk. We also find that short-term uncertainty related to cryptocurrencies affects the prices of BTC, BCH, DOGE, OMG, and LTC, with investors and traders displaying a knee-jerk reaction to policy changes. However, over longer time horizons, all cryptocurrencies become net transmitters of spillovers to uncertainty related to cryptocurrencies. Our study highlights the importance of understanding the interconnectedness and spillover effects within the cryptocurrency market and the potential impact of policy and regulatory changes on the overall level of uncertainty in the market. These findings significantly impact investors, policymakers, and regulators in managing risks in cryptocurrencies' rapidly evolving and interconnected world.

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Appendix

Appendix Table A1: Descriptive Statistics

Time-series	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt.	JB
GPRD	0.0012	-0.0069	1.0157	-0.7316	0.2445	0.0354	4.0977	13.5108*
UCRY	0.0003	-0.0005	0.0512	-0.0796	0.0130	-0.2127	10.6109	648.8605*
BTC	0.0038	0.0090	0.3111	-0.4079	0.1081	-0.4791	4.4455	33.5831*
ETH	0.0051	0.0104	0.4885	-0.5310	0.1423	-0.3687	4.8469	44.1605*
BAT	0.0011	0.0019	0.6095	-0.7069	0.1640	-0.0603	5.4772	68.6847*
BCH	-0.0099	-0.0029	0.8843	-0.7427	0.1751	0.1348	7.7988	257.9619*
BNB	0.0190	0.0069	0.8408	-0.7610	0.1671	0.8249	10.1160	595.8502*
DOGE	0.0157	-0.0166	1.4570	-0.5288	0.2199	2.8491	17.5008	2710.6051*
LTC	0.0007	0.0058	0.7626	-0.7260	0.1521	0.0948	6.7433	156.8731*
OMG	-0.0069	-0.0051	0.8312	-0.7690	0.1850	0.2727	6.1481	113.9918*
XLM	0.0035	-0.0127	0.8045	-0.6638	0.1712	1.0162	7.8477	308.5498*

*Note: * p value < 0.01*

Appendix Table A2: Diagnostic Test Results

Panel A: Normality test results									
	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM
Bartels Test	-1.485	-1.771***	-0.581	-0.76	-0.049	-1.952**	-0.564	-0.892	-1.102
Robust Jarque Bera Test	76.157*	85.031*	121.089*	652.294*	2020.692*	22351.26*	272.775*	234.769*	831.527*
Test of normality SJ Test	6.762*	6.536*	7.01*	11.615*	15.246*	25.969*	8.229*	8.722*	12.032*
Bootstrap symmetry test	-1.15	-0.898	-0.119	-1.041	1.952	4.525*	-0.828	-0.234	2.455**
Difference sign test	0.317	-1.162	0.95	-1.373	0.528	-0.95	-1.162	-1.795*	1.162
Mann-Kendall rank test	-0.859	0.087	-0.82	-0.036	-1.063	-0.752	0.235	-0.016	-0.587
Runs Test	0.612	-0.857	0.367	-0.49	0.122	-2.081	-0.245	-1.224	-0.857
Panel B: Nonlinearity test results									
Teraesvirta NN test	4.0039	3.7089	2.272	3.6997	7.560**	0.5619	4.2773	10.583**	4.799*
White NN test	3.419	2.946	2.2196	6.162**	5.967*	0.788	4.1088	11.159**	3.168
Keenan test	3.953**	6.3290**	0.738	1.084	2.536	0.064	0.0233	0.232	0.617
Tsay test	3.954**	0.395	0.402	0.059	2.537	0.064	0.953	0.496	0.872

*Note: * = 0.01; ** = 0.05; *** =0.10*

Appendix Table A3: Unit Root Tests (Cryptocurrencies)

TS	adf.pvalue	kpss.pvalue	pp.pvalue	adf.statistic	kpss.statistic	pp.statistic
BTC	0.0100	0.1000	0.0100	-5.6874	0.1377	-232.6082
ETH	0.0100	0.1000	0.0100	-6.3772	0.1370	-246.9336
BAT	0.0100	0.1000	0.0100	-7.0004	0.1179	-275.4860
BCH	0.0100	0.1000	0.0100	-7.1474	0.0807	-248.2890
BNB	0.0100	0.1000	0.0100	-6.4622	0.1379	-252.2678
DOGE	0.0100	0.1000	0.0100	-6.5073	0.1000	-230.5368
LTC	0.0100	0.1000	0.0100	-7.2543	0.0619	-252.4033
OMG	0.0100	0.1000	0.0100	-6.5326	0.1101	-251.3423
XLM	0.0100	0.1000	0.0100	-7.5310	0.1833	-256.9216

Appendix Table A4: Spillover Table Between GPRD and Cryptocurrencies

Frequency 1~ 1 Week											
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	1.430	0.010	0.030	0.010	0.010	0.010	0.000	0.000	0.050	0.040	0.020	0.880
BTC	0.000	0.370	0.310	0.190	0.270	0.240	0.140	0.250	0.170	0.200	0.180	9.710
ETH	0.000	0.170	0.330	0.160	0.230	0.200	0.100	0.180	0.160	0.180	0.140	7.660
BAT	0.000	0.140	0.230	0.460	0.260	0.180	0.090	0.180	0.150	0.200	0.140	7.930
BCH	0.000	0.180	0.240	0.180	0.420	0.130	0.110	0.190	0.140	0.140	0.130	7.180
BNB	0.010	0.160	0.250	0.200	0.170	0.420	0.130	0.180	0.190	0.220	0.150	8.350
DOGE	0.000	0.120	0.170	0.090	0.180	0.090	0.470	0.110	0.080	0.100	0.090	5.150
LTC	0.000	0.180	0.250	0.190	0.290	0.170	0.110	0.330	0.140	0.170	0.150	8.180
OMG	0.000	0.170	0.270	0.210	0.240	0.280	0.120	0.230	0.420	0.220	0.170	9.560
XLM	0.000	0.140	0.200	0.200	0.160	0.210	0.120	0.160	0.160	0.410	0.130	7.440
TO_ABS	0.000	0.130	0.190	0.140	0.180	0.150	0.090	0.150	0.130	0.150	1.310	
TO_WTH	0.100	6.930	10.690	7.790	9.930	8.260	5.090	8.170	6.930	8.150		72.050

Frequency 1~ 1- 4 weeks											
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	80.33	0.56	1.53	2.17	0.46	1.66	0.08	0.58	0.93	1.06	0.9	1.26
BTC	0.17	14.55	9.89	5.73	7.84	7.94	3.55	9.31	6.33	7.41	5.82	8.12
ETH	0.22	7.8	12.9	6.12	8.15	6.88	3.34	7.96	6.8	6.42	5.37	7.49
BAT	0.16	5.7	8.19	16.3	7.28	7.03	2.85	6.75	8.13	7.77	5.38	7.51
BCH	0.54	7.32	9.87	6.21	15.6	5.49	3.56	9.02	7.1	6.22	5.53	7.72
BNB	0.35	6.95	8.58	6.59	5.5	14.9	2.96	7.16	6.82	6.76	5.17	7.21
DOGE	0.38	5.65	7.03	4.65	6.63	5.21	22.7	6.54	4.96	6.01	4.71	6.57
LTC	0.36	8.35	9.62	6.37	9.29	7.34	3.75	14.43	7.31	6.57	5.9	8.23
OMG	0.41	6.04	8.65	7.7	7.75	7.83	3.01	7.73	16.07	6.82	5.6	7.81
XLM	0.16	6.38	7.31	7.29	5.94	6.95	3.37	6.6	6.19	15.16	5.02	7
TO_ABS	0.28	5.48	7.07	5.28	5.88	5.63	2.65	6.16	5.46	5.5	49.39	
TO_WTH	0.38	7.64	9.86	7.37	8.21	7.86	3.69	8.6	7.61	7.68		68.9

Frequency 3~ 4 Weeks to inf												
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	8.27	0.06	0.06	0.13	0.04	0.08	0.01	0.22	0.08	0.1	0.08	0.29
BTC	0.03	6.32	3.03	1.84	2.73	1.96	1.87	3.47	1.96	1.94	1.88	7.11
ETH	0.08	4.17	5.62	2.96	3.69	2.87	2.59	3.89	3.04	2.77	2.61	9.84
BAT	0.09	2.73	2.74	6.3	2.2	3.02	1.97	2.79	2.89	3.23	2.17	8.17
BCH	0.14	3.52	3.41	2.46	5.03	1.98	2.38	3.83	2.55	2.05	2.23	8.42
BNB	0.21	3.52	2.75	2.98	2.28	6.71	3.66	3.38	2.9	3.11	2.48	9.35
DOGE	0.02	2.48	2.43	1.93	1.9	2.15	10.39	3.22	1.85	2.47	1.84	6.96
LTC	0.03	4.06	2.7	1.8	2.57	2.15	1.99	5.1	2.12	2.27	1.97	7.43
OMG	0	2.87	2.9	2.88	2.31	2.16	1.76	2.72	5.87	2.34	1.99	7.53
XLM	0.01	3.84	3.63	3.3	2.79	2.92	3.24	3.47	2.99	6.69	2.62	9.88
TO_ABS	0.06	2.73	2.36	2.03	2.05	1.93	1.95	2.7	2.04	2.03	19.87	
TO_WTH	0.23	10.29	8.92	7.65	7.73	7.28	7.35	10.18	7.69	7.66		74.98

Appendix Table A5: Spillover Table Between UCRY and Cryptocurrencies

Frequency 1~ 1 Week												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	2.1300	0.0000	0.0100	0.0000	0.0000	0.0400	0.0000	0.0000	0.0000	0.0000	0.0100	0.3600
BTC	0.0100	0.3600	0.3000	0.1800	0.2600	0.2400	0.1400	0.2500	0.1700	0.2000	0.1700	9.3300
ETH	0.0100	0.1600	0.3200	0.1500	0.2300	0.2000	0.1000	0.1800	0.1600	0.1900	0.1400	7.3400
BAT	0.0000	0.1400	0.2300	0.4600	0.2600	0.1800	0.0900	0.1900	0.1600	0.2100	0.1500	7.8600
BCH	0.0000	0.1800	0.2300	0.1700	0.4000	0.1300	0.1100	0.1900	0.1500	0.1500	0.1300	6.9500
BNB	0.0100	0.1600	0.2500	0.1900	0.1600	0.4100	0.1400	0.1800	0.2000	0.2300	0.1500	8.0900
DOGE	0.0100	0.1100	0.1600	0.0900	0.1700	0.0800	0.4600	0.1000	0.0800	0.1100	0.0900	4.8700
LTC	0.0000	0.1800	0.2500	0.1900	0.2800	0.1700	0.1100	0.3300	0.1400	0.1800	0.1500	8.0400
OMG	0.0100	0.1600	0.2600	0.2100	0.2300	0.2800	0.1200	0.2300	0.4300	0.2300	0.1700	9.2500
XLM	0.0000	0.1400	0.2000	0.2000	0.1500	0.2100	0.1200	0.1600	0.1700	0.4300	0.1400	7.2600
TO_ABS	0.0100	0.1200	0.1900	0.1400	0.1700	0.1500	0.0900	0.1500	0.1200	0.1500	1.3000	
TO_WTH	0.3000	6.5600	10.1900	7.4500	9.3100	8.1200	5.0500	7.8400	6.6200	7.8900		69.3500

Frequency 1~ 1- 4 weeks												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	69.7100	2.0500	2.3500	1.9900	1.8800	2.6900	1.3500	1.7700	2.3200	0.5000	1.6900	2.3700
BTC	0.3000	14.5500	9.9500	5.7700	7.8700	7.9900	3.4800	9.3300	6.3800	7.3200	5.8400	8.1700
ETH	0.3600	7.7800	12.8400	6.1000	8.2000	6.9300	3.2800	8.0000	6.8100	6.3500	5.3800	7.5300
BAT	0.7500	5.7100	8.2600	16.1600	7.2700	7.0100	2.8200	6.6900	8.1000	7.7000	5.4300	7.6000
BCH	0.2800	7.2900	9.9700	6.1300	15.6600	5.6600	3.5600	9.1200	7.2100	6.1700	5.5400	7.7500
BNB	0.7300	6.8600	8.5500	6.4500	5.5600	14.7400	2.9600	7.1700	6.8000	6.7200	5.1800	7.2500
DOGE	0.1900	5.4700	6.8900	4.6200	6.5800	5.3200	22.7700	6.6600	4.9900	6.1900	4.6900	6.5600
LTC	0.4500	8.2600	9.6700	6.2700	9.3400	7.4200	3.8300	14.3500	7.3600	6.5600	5.9200	8.2800
OMG	0.6300	6.0100	8.6700	7.6000	7.8500	7.8800	3.0000	7.7800	15.9500	6.8000	5.6200	7.8600
XLM	0.0900	6.2800	7.2600	7.2500	5.8700	6.9700	3.4600	6.6200	6.2100	15.1700	5.0000	7.0000
TO_ABS	0.3800	5.5700	7.1600	5.2200	6.0400	5.7900	2.7800	6.3100	5.6200	5.4300	50.2900	
TO_WTH	0.5300	7.7900	10.0100	7.3000	8.4600	8.0900	3.8800	8.8300	7.8600	7.6000		70.3600

Frequency 3~ 4 Weeks to inf												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	9.9300	0.1000	0.0900	0.3100	0.0700	0.1600	0.1600	0.0700	0.2700	0.0100	0.1200	0.4700
BTC	0.0400	6.3000	3.0200	1.8800	2.6800	1.9400	1.7900	3.4400	1.9500	1.9000	1.8600	6.9900
ETH	0.0400	4.1800	5.6100	3.0200	3.6900	2.8800	2.5100	3.9200	3.0600	2.7400	2.6000	9.7800
BAT	0.0600	2.7200	2.7100	6.2600	2.1600	2.9500	1.9500	2.7600	2.8400	3.1900	2.1300	8.0100
BCH	0.0300	3.5400	3.4300	2.5100	5.0100	2.0200	2.2700	3.8500	2.5700	2.0000	2.2200	8.3500
BNB	0.0600	3.5400	2.7800	3.0100	2.3600	6.6900	3.6200	3.4500	2.9200	3.1000	2.4800	9.3200
DOGE	0.0100	2.4700	2.4500	1.9600	1.9500	2.2100	10.2300	3.3100	1.8800	2.4900	1.8700	7.0300
LTC	0.0200	4.0500	2.7000	1.8100	2.5700	2.1500	1.9500	5.0700	2.1100	2.2400	1.9600	7.3500
OMG	0.0500	2.8800	2.8900	2.9000	2.3000	2.1500	1.7000	2.7200	5.7900	2.3000	1.9900	7.4700
XLM	0.0100	3.8400	3.6500	3.3400	2.8000	2.9600	3.2300	3.5200	3.0100	6.6700	2.6400	9.9000
TO_ABS	0.0300	2.7300	2.3700	2.0700	2.0600	1.9400	1.9200	2.7000	2.0600	2.0000	19.8900	
TO_WTH	0.1200	10.2500	8.9000	7.7800	7.7300	7.2900	7.2000	10.1500	7.7400	7.5000		74.6500

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THE INFORMATIONAL ROLE OF THE LOAN ONLY CREDIT DEFAULT INDEX (LCDX) ON THE PRICING OF SYNDICATED LOANS

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Abstract

This paper explores the informational role of the Loan Only Credit Default Index (LCDX) on the pricing of syndicated loans. Despite an extensive body of research on credit indices and loan pricing, limited studies have comprehensively assessed the complex relationship between the LCDX and individual loan spreads. Contrary to indices like the CDX, which are largely linked to corporate bonds, the LCDX directly pertains to the syndicated secured loan market, offering valuable insights about the overall credit default market and the cost of credit risk insurance. Preliminary results reveal a pronounced positive correlation between the LCDX spread and the syndicated loan spread, particularly noticeable amongst borrowers with lower credit quality. The paper highlights the LCDX's pivotal role in conveying secondary credit market information, with critical implications for credit risk management and financial regulations.

Keywords: LCDX, Syndicated Loans

1. Introduction

The interplay between various credit indices and loan spreads has long been a subject of interest within the financial sector. Specific attention has been given to two major indices: the Loan Only Credit Default Index (LCDX) and the Credit Default Swap Index (CDX). Theoretically, while the LCDX is linked directly to the syndicated secured loan market, the CDX primarily pertains to corporate bonds, with no direct connection to individual bank loans.

Existing studies on the CDX and its effects on loan pricing have revealed mixed outcomes. Ashcraft and Santos (2009) found an increase in loan spreads for firms that trade Credit Default Swaps (CDSs), with higher spikes for riskier entities. Norden and Wagner (2008), however, argued that CDSs are pivotal in improving price discovery in loan prices, focusing on aggregate loan spread without considering borrower-specific information. Hirtle (2009) posited that banks involved in active hedging charge higher loan spreads. However, previous research has not been without limitations. A predominant drawback lies in the reliance on discrete measures such as the reference entity's trading status and the trading inception date for understanding CDSs.

The current literature does not fully capture the intricate relationship between the LCDX and individual loan spreads, leaving gaps in understanding how banks, with access to unique borrower information, differentiate between good and bad loans (Duffee & Zhou, 2001). This paper aims to cover this gap by studying the information role of the LCDX on the pricing of syndicated loans.

Specifically, we assume two channels through LCDX can potentially affect loan pricing. First, the LCDX provides valuable insights about the overall credit default market. Second, it reflects the cost of credit risk insurance for banks if they need to buy. We assume that the LCDX spread is a superior gauge of macro market trends compared to idiosyncratic firm trading status. It offers a more efficient and informative benchmark for hedging and portfolio diversification, especially as it reflects broader trends in the primary credit market. Thus, The LCDX spread may affect the syndicated loan spread positively and heterogeneously affect borrowers depending on creditworthiness and risk tolerance level.

The preliminary findings indicate significant positive correlation between the LCDX spread and the syndicated loan spread. The economic importance of LCDX is pronounced, especially among borrowers with low quality credit, characterized by unrated status, lower Z-scores, and above-median leverage. The influence of the LCDX appears to strengthen when lenders' risk tolerance deteriorates, and loan terms become riskier. These findings shed light on the nuanced interactions between credit market indices and loan pricing, highlighting the LCDX's substantial role in conveying information about secondary credit default markets. The results support the notion that the LCDX spread reflects broader trends and demands in the primary credit market, offering valuable implications for credit risk management, and financial institutions. For the practical implications, these findings suggest that the LCDX could be a valuable tool for financial institutions in assessing and managing credit risk more effectively. For instance, by monitoring LCDX trends, banks and other lenders could adjust their credit offerings and risk assessment models to better align with market conditions, thereby enhancing their risk management strategies. For financial regulations, regulators could use the LCDX as an early-warning system to identify emerging risks in the credit markets, allowing for timely intervention to prevent market instability. The findings could also inform the development of regulatory policies that more accurately reflect the realities of the credit market, particularly in terms of capital requirements and risk assessment for financial institutions.

2. Hypotheses Development

Financial markets continually evolve to meet the necessities of participants, with lenders frequently adopting new products to effectively shift credit risks to willing absorbers. Recent developments in credit derivative contracts have enabled lenders to maintain control rights over loans, offering a more flexible risk mitigation approach compared to earlier loan sales, securitization, or syndications. The most prevalent of these, the Credit Default Swap (CDS), allows bondholders and banks to hedge default risks by paying periodic premiums to an insurer. These contracts define specific terms such as the reference entity (borrower), obligation (bond or loan), trigger events (bankruptcy, failure to pay, etc.), and contract duration. The CDS market experienced significant growth, ballooning from $2 trillion in 2002 to $60 trillion in 2007 (Weistroffer, 2009).

CDSs are believed to enhance liquidity flow and market transparency by providing new insights into traded companies, which positively influences the underlying market. Firms involved in CDS trading can secure loans with higher leverage and longer maturities (Saretto & Tookes, 2013). Differing from standard insurance, CDSs don't require the buyer to hold an underlying debt exposure, enabling both hedging and speculative opportunities based on the perceived credit quality of the reference obligation. In situations of credit scarcity, CDSs offer essential information for credit portfolio management and risk diversification. Under the Basel II framework, banks' Tier 1 capital is linked to risk-weighted assets, and regulators acknowledge CDSs in the evaluation of capital ratios, provided the protection seller's rating surpasses that of the banks (Duncan, 2006). Additionally, CDSs avoid the tax and accounting complexities associated with loan sales, thereby reducing transaction costs.

Interestingly, research also highlights some negative impacts of Credit Default Swaps (CDSs). Hirtle (2009) contends that the advantages of CDSs are somewhat constrained. Contrary to the effects observed in credit sales or securitization, banks do not necessarily expand their credit offerings when they employ CDS protection. This expansion in credit availability tends to be restricted to only substantial borrowers of term loans. Furthermore, Bolton and Oehmke (2011) suggest that tradable

CDS contracts enhance lenders' protection against negative credit events, consequently strengthening their negotiating position. This results in lenders becoming more stringent in negotiations, often reluctant to engage in costly measures that might benefit the borrower's financial situation, leading to the emergence of the 'empty creditor' issue. Additionally, Duffee and Zhou (2001) have developed a theoretical model addressing both CDSs and credit sales, raising concerns that the CDS market might negatively impact the market for loan sales.

Parlour and Winton (2013) outlined scenarios in which lenders might opt to sell a loan or purchase a Credit Default Swap (CDS). Their analysis suggests that for higher-risk loans, the option of selling the loan is more prevalent than using CDSs; conversely, for lower-risk loans, CDSs are more commonly utilized than selling the loans. They also observed that lenders' motivation to monitor borrowers diminishes when they secure CDSs. Chakraborty et al. (2023) provided evidence for the 'empty creditor' issue, indicating that lenders might engage in moral hazard behaviours, particularly in instances of borrowers violating loan covenants. This issue of moral hazard arises when banks intentionally issue low-quality loans without the intent to retain them (Gorton & Pennacchi, 1995). Additionally, Martin and Roychowdhury (2015) discovered that when a loan is retained with CDS coverage, lenders show reduced incentives to monitor borrowers, leading to less conservative reporting practices. Hence, retaining a loan, as opposed to selling it, can mitigate the moral hazard concern. In the context of CDS-traded firms, it is observed that lenders are less vigilant in monitoring early-stage loan violations and tend to impose higher interest rates following such violations. Moreover, the issue of adverse selection becomes prominent when the cost of insolvency significantly influences the decision to sell a loan (Carlstrom & Samolyk, 1995). This adverse selection issue is primarily driven by the unobservable quality of the loan.

Several empirical research has shed light on how Credit Default Swap (CDS) contracts influence the dynamics between lenders and borrowers. Notably, CDSs have been found to enhance the credit quality of borrowers, a benefit attributed to the lender's ability to hedge risk (Allen & Carletti, 2006). Furthermore, Parlour and Winton (2013) indicate that CDSs play a significant role in shaping the lender-borrower relationship, particularly benefiting those borrowers with strong credit profiles. However, the impact of CDSs isn't exclusively positive. Studies suggest that CDSs can negatively affect these relationships (Duffee & Zhou, 2001; Morrison, 2005), potentially escalating bankruptcy risks for borrowers (Saretto & Tookes, 2013; Subrahmanyam et al., 2014).

In this research, the focus is placed on the Loan Only Credit Default Swap Index (LCDX), which encompasses syndicated senior and secured loans. The study aims to explore how the spread of the LCDX impacts the costs of underlying loans. This spread is instrumental in providing lenders with critical insights into the secondary credit default market, as well as fair market costs for credit risk protection. Norden and Wagner (2008) highlight that CDSs, being direct measures of hedging activities, exert a tangible influence on loan pricing. This is particularly relevant, as they offer a reliable benchmark for assessing debt costs, even for companies that are not actively traded. Their research underscores the dominant explanatory power of CDSs over traditional bond markets and other non-CDS factors in determining loan prices, emphasising its significance as a novel determinant of loan costs due to its more accurate reflection of lending relationships. However, it is important to note some limitations in their approach. The CDX spread in their study is derived from the CDS spread quotes of a single large investment bank, potentially not capturing the broader market perspective. Furthermore, the CDS spread they use encompasses unsecured corporate debts, including both bonds and loans, making it a less precise and relevant measure compared to the LCDX for senior syndicated and secured loans. Additionally, their method involves using time series data to calculate average loan spreads, without accounting for borrower-specific variations.

Similarly, Hirtle (2009) discovered that banks often employ CDSs in conjunction with other hedging strategies. Banks engaging in such comprehensive hedging practices tend to raise the spreads on larger loans as a means to balance out their hedging costs. This leads to the argument that banks consider the expense associated with transferring credit risk when issuing new loans and adjust their pricing strategies accordingly. In this context, the LCDX serves as a reliable benchmark for gauging this cost. Consequently, as the cost of credit insurance borne by lenders rises, it translates into higher interest rates for borrowers. Based on this understanding, we propose the following hypothesis:

H1: The loan-only credit default swap market positively affects the individual loan spread.

Ashcraft and Santos (2009) observed that entities referenced in CDS contracts typically incur higher interest rates than those not involved in CDS trading. This elevation in rates varies across different firms, being particularly pronounced for firms perceived as riskier or less transparent. They suggest that the reduced monitoring efforts by lead arrangers for loans insured under CDSs contribute to this phenomenon. As a result, a higher spread is demanded by participants to compensate for the potential moral hazard associated with the lead arrangers, especially in the case of the loans specifically referenced in the CDS contracts. Additionally, Bolton and Oehmke (2011) contend that CDSs are more advantageous for borrowers characterised by high volatility and lower credit quality. Following these, we propose the following hypothesis:

H2: The loan-only credit default swap market impacts loan spread differently based on the underlying credit risks of the borrower.

The decision of banks to incorporate credit derivatives in their loan strategies is significantly influenced by the resources at their disposal. Major lending institutions, with ample resources, are likely to leverage the credit derivative markets, integrating this information into their loan pricing models. Furthermore, the number of lenders participating in a loan facility also plays a crucial role. Lead arrangers often take this factor into account when deciding whether to acquire credit derivatives for a particular loan. We contend that in scenarios where loans are highly concentrated, the motivation for lenders to procure credit insurance protection intensifies. Consequently, we propose the following hypothesis:

H3: The loan-only credit default swap market influences the loan spread variably, depending on the characteristics of the lenders' risk tolerance.

3. Data and Model

For this study, panel data is utilized, gathered from four distinct sources. Loan level data is procured from Thomson Reuter's Dealscan, and the daily spread for the 5-year on-the-run LCDX is taken from the Markit database. By aligning these two databases with the loan initiation date, the analysis is restricted to senior, secured, and syndicated loan facilities that involve multiple lenders. Additional borrower information is drawn from Compustat, linked with Dealscan using the connection provided by (Chava and Roberts, 2008). The analysis focuses on the loan facility, as each facility's loan spread defines the borrower's varying needs. We exclude all financial firms from the sample. We conduct the analysis through multiple regressions and construct the empirical model as follows:

$$loan\ spread_{i,t} = \beta_0 + \beta_1 LCDX\ spread_t + \delta * Loan\ characteristics_{i,t} + \theta * Borrower\ characteristics_{i,t-1} + \vartheta * Borrower\ industry\ fixed\ effects + \tau * Deal\ Purpose\ Dummies + \varphi * Top\ 10\ lead\ dummies + \varepsilon_{i,t} \quad (1)$$

The dependent variable is the all-in-drawn loan spread in basis points, representing the loan price. The key variable of interest is the LCDX spread, specifically the on-the-run LCDX spreads in basis points for five years. These are believed to provide the best market price for immediate credit risk protection. According to (Norden and Wagner, 2008), banks are increasingly efficient in reflecting CDS market information in loan pricing, justifying the use of the contemporaneous LCDX spread at the time of loan issuance. In recognizing the importance of a borrower's unique credit quality, we control for the borrowers' characteristics such as firm sales as a measure for size, leverage as a measure of indebtedness, interest coverage as a measure for the ability to repay, ROA as a measure for profitability, cash flow volatility as a measure for risk, Tobin's Q as a measure for growth, and R&D expenses as a measure for capital expenses. Further, to control for any borrower's industry idiosyncrasies, we include industry fixed effects; to control for year differences, we include year dummies, and to control supply-side effect, we include the top 10 banks[1]' dummy variables. Furthermore, we control for all other loan characteristics including loan size, maturity, loan revolver, refinancing terms as well as the indicator variables for different loan purposes.

4. Result

The study's results, obtained after restricting the sample to 1,768 unique loan facilities issued to non-financial firms as secured, syndicated loans, present intriguing insights. Table 1 offers summary statistics.

Table 1: Summary statistics

		N	Mean	Sd	Media	p25	p75
All in-drawn (Spread)	Basis Points	1768	301.66	143.51	275.00	200.00	375.00
LCDX (Spread)	Basis Points	1768	478.68	358.98	380.70	286.80	478.20
Borrower characteristics							
Log (Sale)	Natural log of sales	1768	5.75	1.35	5.73	4.86	6.60
Tobin's Q	Total Market value/Total Assets	1768	1.45	0.73	1.25	1.04	1.61
R&D rate	RD expense/Sales	1768	0.01	0.05	0.00	0.00	0.00
ROA	Net Income/Total Assets	1768	0.00	0.06	0.01	0.00	0.02
Leverage	Total debt/Total Assets	1768	0.35	0.25	0.31	0.16	0.49
Log (Cash flow volatility)	Natural log of standard deviation of Operating cash flows	1768	-3.19	1.52	-3.31	-4.18	-2.35
Interest rate coverage	Operating Income After Depreciation/Interest Expenses	1768	31.76	466.72	3.17	1.24	8.23
Investment grade	Long term SP rating above BBB	1768	0.06	0.23	0.00	0.00	0.00
High yield grade	Long Term SP rating below BBB	1768	0.49	0.50	0.00	0.00	1.00
Loan characteristics							
Log (loan amount)	Natural log of loan amount	1768	6.00	1.19	5.93	5.20	6.82
Log (loan maturity)	Natural log of loan maturity in months	1768	3.86	0.49	4.09	3.65	4.10
Loan revolver dummy	If the loan is a revolver loan	1768	0.65	0.48	1.00	0.00	1.00

[1] Top 10 banks: JP Morgan, Bank of America Merrill Lynch, US bank, Bank of America, Royal Bank of Scotland Plc, Wells Fargo & Co, Citibank, Deutsche Bank AG, BNP Paribas SA, SunTrust Bank

		N	Mean	Sd	Media	p25	p75
Refinancing indicator	If the loan is for refinancing	1768	0.93	0.26	1.00	1.00	1.00
Lender characteristics		1768	0.29	0.45	0.00	0.00	1.00
Top10	If the lenders belong to top 10	1768	0.29	0.45	0.00	0.00	1.00
Number of lenders (Facility)	Number of participating banks in the facility	1768	8.45	6.84	6.00	4.00	11.00

Note: This table reports summary statistics for all variables used in this study.

In Table 2, Pearson correlations reveals a positive association between loan cost and the LCDX, with a 0.23 correlation significant at the 5 percent level. This relationship is further confirmed as all control variables significantly correlate with the loan spread, legitimizing the variable selection.

Table 2: Pearson's correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	All in-drawn (Spread)	1														
(2)	LCDX (Spread)	**0.23**	1													
(3)	Log (Sale)	**-0.23**	**-0.04**	1												
(4)	Tobin's Q	**-0.14**	**-0.12**	**-0.07**	1											
(5)	R&D rate	**0.06**	0	**-0.09**	**0.04**	1										
(6)	ROA	**-0.19**	**-0.18**	**0.1**	**0.16**	**-0.09**	1									
(7)	Leverage	**0.23**	**0.04**	**0.02**	**-0.08**	**-0.03**	**-0.17**	1								
(8)	Cash flow volatility	**0.26**	**0.15**	**-0.3**	**-0.11**	**0.11**	**-0.27**	**0.18**	1							
(9)	Interest rate coverage	**-0.04**	-0.01	-0.01	**0.09**	-0.02	**0.04**	**-0.08**	**-0.03**	1						
(10)	Log (loan amount)	**-0.1**	**-0.13**	**0.57**	0.02	**-0.05**	**0.09**	**0.14**	**-0.1**	0.01	1					
(11)	Log (loan maturity)	**0.03**	**-0.23**	0	**0.04**	**-0.03**	**0.1**	**0.05**	**-0.09**	0	**0.15**	1				
(12)	Loan revolver dummy	**-0.19**	**-0.04**	**-0.07**	0	**-0.02**	0.01	**-0.12**	**-0.06**	0	**-0.07**	**0.11**	1			
(13)	Refinancing indicator	**-0.03**	-0.02	**0.13**	**-0.11**	**-0.07**	0	**0.1**	**-0.07**	**-0.04**	**0.16**	**0.17**	**0.13**	1		
(14)	Investment grade	**-0.33**	-0.02	**0.42**	**-0.04**	-0.02	**0.07**	**-0.07**	**-0.12**	-0.02	**0.23**	**-0.14**	0.01	0.01	1	
(15)	High yield grade	**0.2**	0	**0.16**	**-0.08**	-0.02	**-0.07**	**0.34**	**0.06**	**-0.03**	**0.23**	**0.14**	**-0.07**	**0.1**	**-0.39**	1

Note: This table reports the correlations between the dependent variable, the variable of interest, and borrower characteristics. The variable descriptions are in the appendix. The values in bold represent correlations that are significant at 5%.

Table 3 exhibits the baseline regression, displaying a positive and significant effect of the LCDX spread at 1 percent. The influence of LCDX remains substantial, with a 0.21 standard deviation increase in loan spread corresponding to a one standard deviation increase in LCDX (0.09*360.47/155.11). Explanatory power is measured at 41%, supporting Hypothesis 1. Nearly all control variables align with expectations, except interest coverage and high yield rating. As hypothesized, investment-grade, profitable, and growth companies pay lower interest rates, whereas riskier borrowers pay more.

Table 3: Baseline analysis in loan level

Variables	All in-drawn (Spread)	
LCDX (Spread)	**0.10*** **	**0.09*** **
(P value of one-sided test)		**-0.003**
Borrower characteristics		
Log (Sale)		10.86**
Tobin's Q		-21.83***
R&D rate		251.70*
ROA		-216.86***
Leverage		65.57***
Log(Cash flow volatility)		11.19***
Interest rate coverage		0
Investment grade		-88.89***
High yield grade		6.39
Loan characteristics		
Log (loan amount)		-12.15**
Log (loan maturity)		-27.10**
Loan revolver dummy		-59.77***
Refinancing indicator		-26.62*
Constant	254.34***	509.56***
Observations	**1,768**	**1,768**
R-squared	**0.06**	**0.41**
Industry FE	NO	YES
Time FE	NO	YES
Deal purpose dummies	NO	YES
Top 10 Lender dummies	NO	YES

*Note: This table shows the univariate and multivariate OLS results. The dependent variable is the loan interest payment over LIBOR (All-in-drawn spread). The key independent variable is Loan only Credit Default Swap spread (LCDX). The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significance at the 1, 5, and 10% levels respectively.*

Table 4 demonstrates a split by credit quality, revealing the LCDX's high significance for distressed, unrated, and highly indebted firms but not for safe, rated, and low-indebted firms. Columns 1 and 2 divide the sample according to the Altman Z-score, with Column 1 focusing on distressed firms and Column 2 on firms deemed financially stable. Columns 3 and 4 categorize the sample by credit rating; results for unrated firms are in Column 3, while Column 4 encompasses rated firms. Additionally, Columns 5 and 6 distinguish the sample based on whether firms have above or below median leverage. This supports Hypothesis 2, showing heterogeneous effects across borrower types. Table 5 considers top lenders' ability to purchase the LCDX and how loan concentration (measured by the number of lenders in the syndicate) may affect the results.

Table 4: Sensitivity of LCDX to Borrowers' risk characteristics

Variables	z<1.81	z>2.99	No SP rating	SP rating	above Leverage	below Leverage
LCDX (Spread)	**0.07*** **	**0.01**	**0.08** **	**0.05**	**0.09** **	**0.02**
Borrower characteristics						
Log (Sale)	10.34*	11.4	14.22**	5.93	11.30**	13.58**
Tobin's Q	-16.61	-19.75***	-16.90***	-28.08***	-17.68**	-20.79***
R&D rate	403.29***	66.69	148.08	364.96**	138.38	245.48
ROA	-173.65***	-97.23	-307.13	-212.86***	-110.28*	-630.85***
Leverage	54.09**	114.80***	92.20***	84.61***	68.25**	-33.14
Log(Cash flow volatility)	11.76***	6.65	13.83***	9.00**	8.42***	12.88***
Interest rate coverage	-0.23	0	0	0.02	-1.55***	-0.00*
Investment grade	-93.20***	-146.35***			-77.19***	-97.53***
High yield grade	1.34	-3.33			6.76	11.38
Loan characteristics						
Loan amount	-13.45**	-8.49	-0.47	-20.32***	-27.07***	-1.06
Loan maturity	-37.80***	-23.82	-39.55**	1.87	-39.38***	-14.28
Loan revolver	-66.98***	-19.68**	-63.25***	-51.07***	-63.02***	-56.87***
Refinancing	-8.14	-25.34	-17.66	-11.49	2.03	-33.29
Constant	575.68***	421.35***	501.49***	442.57***	575.88***	286.20**
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Deal purpose dummies	YES	YES	YES	YES	YES	YES
Syndication Dummy	YES	YES	YES	YES	YES	YES
Top 10 Lender dummies	YES	YES	YES	YES	YES	YES
Observations	1,245	288	801	967	977	791
R-squared	0.4	0.59	0.39	0.49	0.43	0.47

*Note: This table shows the results for the subsample analyses. Columns 1 and 2 show the results for the borrower's risk tolerance by its Z score. Columns 3 and 4 show the results for borrowers with non SP and SP ratings. Columns 5 and 6 show the results for above and below median leverage of borrowers. All of the lender's, borrower's, and the loan's characteristics as well as time and borrower industry fixed effects are controlled for. The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significances at the 1, 5 and 10% levels respectively.*

In Table 5, Columns 1 and 2 present the regression analyses for the top 10 lenders compared to lenders outside this group. Column 3 details the findings for the diversified lending group, while Column 4 focuses on the concentrated lending group. The result suggests that larger banks factor in the LCDX spread when setting their loan prices. Notably, the LCDX spread maintains a significant positive correlation with loans from the concentrated group, whereas its significance diminishes for loans from the diversified group. This indicates that loan syndication, which allows for credit risk sharing, diminishes the importance of credit protection as measured by the LCDX. Conversely, for lenders facing credit concentration risk, protection against default risk assumes greater importance. Therefore, the impact of the LCDX spread is more pronounced in such scenarios.

Table 5: Sensitivity of LCDX to Lenders' risk characteristics

Variables	TOP 10 lenders	Non TOP10	Above number of lenders	Below number of lenders
LCDX	**0.16*** **	**0.05**	**-0.01**	**0.13*** **
Borrower characteristics				
Log (Sale)	12.83*	9.93*	6.42	16.53**
Tobin's Q	-12.26	-27.21***	-24.69***	-13.24
R&D rate	181.4	366.61**	444.05*	163.67
ROA	-317.25**	-180.57***	-143.04	-188.53**
Leverage	56.06	85.57***	42.46*	72.94**
Log(Cash flow volatility)	15.91***	11.96***	8.89***	11.73***
Interest rate coverage	-0.04**	0	0	0
Investment grade	-82.35***	-102.93***	-81.37***	-120.53***
High yield grade	-16.86	7.95	2.5	8.95
Loan characteristic				
Log (loan amount)	-12.14*	-23.97***	-17.13***	-7.31
Log (loan maturity)	-17.51	-32.63**	1.79	-41.81***
Loan revolver dummy	-81.79***	-59.57***	-33.39***	-86.43***
Refinancing indicator	-0.95	-44.77**	-10.11	-34.19
Time FE	YES	YES	YES	YES
Deal purpose dummies	YES	YES	YES	YES
Syndication Dummy	YES	YES	YES	YES
Top 10 Lender dummies	NO	NO	YES	YES
Constant	522.55***	567.04***	544.44***	572.78***
Observations	514	1,254	1,034	734
R-squared	0.43	0.39	0.44	0.44

*Note: This table shows the results for the subsample analyses by lender's level of risk tolerance. Columns 1 and 2 show results for loans issued by top 10 lenders and non-top 10 lenders. Columns 3 and 4 show the results for the above and below median of number of lenders in the facility. All of the lender's, borrower's, and the loan's characteristics as well as time and borrower industry fixed effects are controlled for. The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significances at the 1, 5 and 10% levels respectively.*

Table 6 delineates the effect on revolving and non-revolving loans. The LCDX remains significantly positive, but its economic significance doubles for riskier non-revolving term loans, indicating a heightened significance of LCDX effect for riskier loans. Furthermore, the LCDX plays a more crucial role in refinancing loans.

Table 6: Sensitivity of LCDX to loans' risk characteristics

VARIABLES	Revolver loan	Non-Revolver loan	Refinancing loan	Non-refinancing loan
LCDX	**0.07*** **	**0.14** **	**0.09*** **	-0.02
Borrower characteristics				
Log (Sale)	6.36*	16.66**	11.19**	20.48
Tobin's Q	-19.23***	-25.26***	-22.47***	-20.1
R&D rate	109.51	411.49*	278.04*	-308.5
ROA	-187.34***	-227.39**	-234.90***	-237.54
Leverage	64.65***	67.88**	77.48***	-161.85**
Log(Cash flow volatility)	8.00***	14.41***	10.54***	74.04***
Interest rate coverage	0	0.01	0	-0.04
Investment grade	-62.89***	-120.81***	-91.06***	8.13
High Yield grade	10.04	0.51	2.06	48
Loan characteristic				
Log (loan amount)	-5.68	-20.64**	-11.42**	-10.16
Log (loan maturity)	-32.68***	-26.86	-18.99*	-52.34
Loan revolver dummy			-55.63***	-103.92**
Refinancing indicator	-17.37	-49.85		
Constant	429.57***	395.62**	389.55***	640.33***
Time FE	YES	YES	YES	YES
Deal purpose dummies	YES	YES	YES	YES
Syndication Dummy	YES	YES	YES	YES
Top 10 Lender	YES	YES	YES	YES
Observations	1,151	617	1,636	132
R-squared	0.48	0.36	0.4	0.73

*Note: This table shows the results for the subsample analyses by the lender's level of risk tolerance. Columns 1 and 2 show the results for revolver and non-revolver loans, and Columns 3 and 4 show the results for refinancing loan and non-refinancing loans. All of the lender's, borrower's and the loan's characteristics as well as time and borrower industry fixed effects are controlled for. The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significances at the 1, 5 and 10% levels respectively.*

The validity of the LCDX spread as a benchmark is tested by relaxing restrictions on loan security and syndication. Columns 1 to 3 in Table 7 show that the LCDX spread loses significance when applied outside of its coverage loans, indicating it might not be an appropriate benchmark for other loan types.

Table 7: Sensitivity of LCDX to non-secured and non-syndicated loans

Variables	SSS	Non-secured	No-syndicated
LCDX	0.09***	0	0.13
Borrower characteristics			
Log (Sale)	10.86**	-9.16*	4.6
Tobin's Q	-21.83***	-17.63***	-10.93
R&D rate	251.70*	-36.59	-24.43
ROA	-216.86***	154.09	-159.82
Leverage	65.57***	92.20*	40.91
Log(Cash flow volatility)	11.19***	9.03**	26.08***
Interest rate coverage	0	0	0.01
Investment grade	-88.89***	-0.48	-93.74
High Yield grade	6.39	26.72	-17.11
Loan characteristic			
Log (loan amount)	-12.15**	-4.16	11.17
Log (loan maturity)	-27.10**	20.91**	-11.08
Loan revolver dummy	-59.77***	-25.85**	-75.99***
Refinancing indicator	-26.62*	-19.58	26.75
Time FE	YES	YES	YES
Deal purpose dummies	YES	YES	YES
Syndication Dummy	YES	YES	YES
Top 10 Lender dummies	YES	YES	YES
Constant	509.56***	405.86***	182.67
Observations	1,768	777	347
R-squared	0.41	0.44	0.52

*Note: This table shows the results for the subsample analyses by loan characteristics. Columns 1 shows the results for secured, syndicated, senior loans; Column 2 shows the results for non-secured, syndicated, senior loans; and Columns 3 shows the results for secured, non-syndicated, senior loans. All of the lender's, borrower's and the loan's characteristics as well as time and borrower industry fixed effects are controlled for. The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significances at the 1, 5 and 10% levels respectively.*

The study also refers to the 2008 subprime mortgage crisis, highlighting concerns regarding excessive risk-taking and counterparty risk in Table 8. This leads to the examination of whether insured entities need to worry about the insurer's ability to fulfil credit default claims.

Table 8: Sensitivity of LCDX during the crisis

Variables	2008	2009	2010
LCDX	0.12***	0.01	0.17**
Borrower characteristics			
Log (Sale)	27.11***	31.16**	1.73
Tobin's Q	5.1	-47.91***	-23.17*
R&D rate	401.78**	-77.73	284.9
ROA	-192.8	-142.8	-177.10**
Leverage	88.86*	139.60***	44.65
Log(Cash flow volatility)	10.40*	9.3	15.49***
Interest rate coverage	0	-0.29**	-0.05**
Investment grade	-130.73***	-32.19	-95.28***
High Yield grade	-0.73	34.07	-10.76
Loan characteristics			
Log (loan amount)	-13.18	-45.71***	1.25
Log (loan maturity)	-20.06	12.42	-38.18*
Loan revolver dummy	-77.78***	-58.39**	-57.58***
Refinancing indicator	-24.27	-74.81	-36.94
Time FE	NO	NO	NO
Deal purpose dummies	YES	YES	YES
Syndication Dummy	YES	YES	YES
Top 10 Lender dummies	YES	YES	YES
Constant	348.14***	479.65***	629.44***
Observations	314	299	459
R-squared	0.44	0.37	0.44

*Note: This table shows the results for the subsample analyses by years. Column 1 shows the results for before the crisis, Column 2 shows the results for during the crisis, and Column 3 shows the results for after. All of the lender's, borrower's and the loan's characteristics as well as time and borrower industry fixed effects are controlled for. The coefficient estimates are based on the robust standard errors clustered at the borrower level. The ***, **, and * represent significances at the 1, 5 and 10% levels respectively.*

Lastly, a sensitivity analysis across different time periods reveals that the significance of the LCDX spread holds for 2008 and 2010 but loses its importance in 2009. This finding underlines the LCDX's sensitivity to market trust, showing that as the market recognizes an insurer's inadequacy and doubts its capacity, the information in the LCDX spread ceases to be relevant.

5. Limitation and Future Research

This research acknowledges certain limitations. Primarily, the focus on senior, secured, and syndicated loans might not fully capture the complexities of other loan types and their interplay with the LCDX. Moreover, a potential endogeneity issue, especially regarding simultaneity, is noteworthy. The bidirectional relationship between the LCDX and individual loan spreads suggests that while the LCDX could influence loan spreads by setting benchmarks or through market sentiment, changes in individual loan spreads due to firm-specific news or broader economic factors could also impact the LCDX's value. This interdependence highlights the need for further investigation into the causal dynamics between the LCDX and loan spreads.

Additionally, the study's timeframe could raise questions about the temporal context of our findings, particularly considering significant economic events like the subprime mortgage crisis between 2007 and 2012. This period's selection is vital, given the heightened market volatility and credit risk reassessment during these years, which could profoundly affect our study's results. Future research should aim to justify this period selection more robustly and consider how varying market conditions like COVID or a more stable economic environment might influence the outcomes.

Furthermore, the analysis is constrained by the available data's scope and depth, possibly omitting crucial market dynamics or a complete spectrum of credit instruments such as the CDX. Future studies could explore the impact of the LCDX on a wider variety of loan types, including subordinated debts, under different market conditions. It would also be beneficial to assess the potential long-term effects of LCDX movements on credit market stability and delve deeper into the LCDX's implications for smaller, less creditworthy borrowers.

6. Conclusions

In this study, we investigate the influence of the LCDX spread on contemporary loan issuances, emphasizing its role as a market health indicator and a signal of credit risk protection costs for lenders. The findings reveal that as the LCDX spread rises, the loan spread also increases, with a more significant effect for riskier borrowers. The information role of the LCDX, however, is sensitive to loan types and market cycles, losing significance for loans outside its coverage. It suggests that the LCDX may not be an appropriate benchmark for certain loans and that information-advantaged lenders may react selectively to the most credible information. In conclusion, the LCDX's role is significant for senior, secured, and syndicated loans, particularly when lenders are likely to seek credit protections, highlighting a complex relationship that warrants further investigation.

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INFECTIOUS DISEASE AND ASYMMETRIC INDUSTRIAL VOLATILITY

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Abstract

We examine the time-varying effect of stock market volatility due to infectious diseases on industrial sectors in the US from 2012 to 2021 in three sub-periods: the whole sample till COVID-19, during COVID-19 period before and after the Pfizer and Biontech vaccine announcement, respectively. We extend the current literature by exploring the diverse impact of infectious disease equity market volatility index (EMV-ID) on market index and various industrial sectors and decomposing industrial volatility into good and bad volatility to quantify how good and bad components vary in response to the transmission of shocks due to infectious diseases. The results show that the transmission of volatile shocks from the stock market strongly enhances the bad components of industrial volatility before the outbreak of COVID-19 but the good component of industrial volatility during COVID-19 before the Pfizer and Biontech vaccine announcement. The positive transmission of volatile shocks from EMV-ID towards the industrial volatility strengthens and gains momentum as the industrial volatility transits from bearish (lower quantiles) towards the bullish (higher quantiles) conditions irrespective of the period considered. We conclude that the relationship between infectious disease equity market volatility and industrial volatility depends on the good and bad volatile components and their respective conditions at different quantiles.

Keywords: Infectious disease equity market volatility, good volatility, bad volatility, S&P 500, vaccine announcement

1. Introduction

The global spread of the coronavirus (COVID-19) and accompanying containment measures enhanced uncertainties in the global economy and international financial markets at an unprecedented level. With the expanding impact of the pandemic, a growing number of studies have investigated the influence of the pandemic on stock markets. Towards this end, numerous studies have established that the pandemic has caused extreme volatility in the stock markets of affected countries (Topcu and Gulal, 2020; Acharya et al., 2021; Al-Awadhi et al., 2020; Baek et al., 2020; Engelhardt et al., 2021; Kapar et al., 2021; Kucher et al., 2021; Rouatbi et al., 2021). These pandemic-induced equity market disturbances are found to be more severe than previous outbreaks of infectious diseases such as SARS, MERS, Swine flu and Ebola virus (Baker et al., 2020; O'Donnell et al., 2021, Bai et al., 2021). Similarly, compared to the global financial crisis (GFC) in 2008, the evidence suggests that COVID-19 has more intensified impact across countries and stock market sectors (Choi, 2020; Shehzad et al., 2020).

Although global stock markets are adversely affected by the pandemic, the impact is found to be asymmetric across sectors (Mazur et al., 2021; Kapar et al., 2022; Gräb et al., 2021; He et al., 2020; Bradley and Stumpner, 2021). For instance, Gräb et al. (2021) show that stock market sectors that hit the hardest by the pandemic gained more in response to positive vaccine-related announcements. Bradley and Stumpner (2021) estimate that the spread between the best and worst-performing sectors widened from 27 percentage points to 80 percentage points within the year of the outbreak of the COVID-19 pandemic. Some industries, such as airline, travel, banking, insurance, and energy witnessed considerable losses, whereas industries like airfreight, household appliances, computers and electronics benefited from the pandemic.

Understanding how different pandemic-induced shocks impact industrial sectors is crucial for investors and businesses to make optimal investment and hedging decisions. This requires an in-depth analysis at the industrial level, which is presently lacking in literature. We fill this gap in the literature and investigate the effect of equity market volatility due to infectious diseases on industrial volatility (IV hereafter). This study, therefore, broadens our understanding of the diverse impact of infectious diseases on industrial sectors in the US.

To better capture the impact of infectious diseases on industrial sectors, we use the newly developed Infectious Disease Equity Market Volatility Index (EMV-ID hereafter) constructed by Baker et al. (2020), which tracks US equity market volatility caused by infectious diseases. EMV-ID has been widely employed in recent empirical studies to explore the impact of equity market volatility due to infectious diseases on numerous factors, such as commodity returns (Long and Guo, 2022), stock market returns (Ozkan et al., 2022; Gohar et al., 2022), Islamic stocks (Salisu and Sikiru, 2020), energy market (Salisu and Adediran, 2020), sports economy (Guo et al., 2022), public sentiment (Meng et al., 2021), corporate activities (Suleman and Yaghoubi, 2022) and others.

We contribute to the literature by employing this newly developed EMV-ID index to examine its heterogeneous effect on the volatility of ten industrial sectors in the US (i.e., consumer services, financials, health care, industrials, materials, oil and gas, real estate, technology, telecommunication, and utilities) and general market index. Further, we extend the literature by exploring the impact of infectious diseases on various industrial sectors as well as market index and decomposing industrial volatility into good and bad volatility to quantify how good and bad components vary in response to the transmission of shocks due to infectious diseases. Our motivation to study the good and bad volatility of spillovers among stock sectors is due to the evidence suggesting that volatility in financial markets is highly sensitive to good and bad returns. Moreover, this helps to identify whether a specific sector is more prone to infectious disease volatility that will be useful for investors, portfolio managers and regulators. Finally, to better understand the interrelationship between EMV-ID and IV, we examine the association at different quantiles using quantile regression.

Hence, the aim of this study is to examine the time-varying effect of stock market volatility due to infectious diseases on industrial sectors in the US from 2012 to 2021 in three sub-periods: the whole sample till COVID-19, during COVID-19 period before and after the Pfizer and Biontech vaccine announcement, respectively. We find that the transmission of volatile shocks from the stock market more strongly enhances the bad components of industrial volatility before the outbreak of COVID-19 but the good component of industrial volatility during COVID-19 before the vaccine announcement. The positive transmission of volatile shocks from the EMV-ID towards the industrial volatility is stronger when the industrial volatility transits from bearish (lower quantiles) towards the bullish (higher quantiles) conditions irrespective of the period considered. Overall, we conclude that the relationship between EMV-ID and IV depends on the good and bad volatile components and their respective conditions at different quantiles.

The rest of the paper is organized as follows. Section 2 presents the data, Section 3 the methodology, and Section 4 the findings. Finally, a conclusion is provided in Section 6.

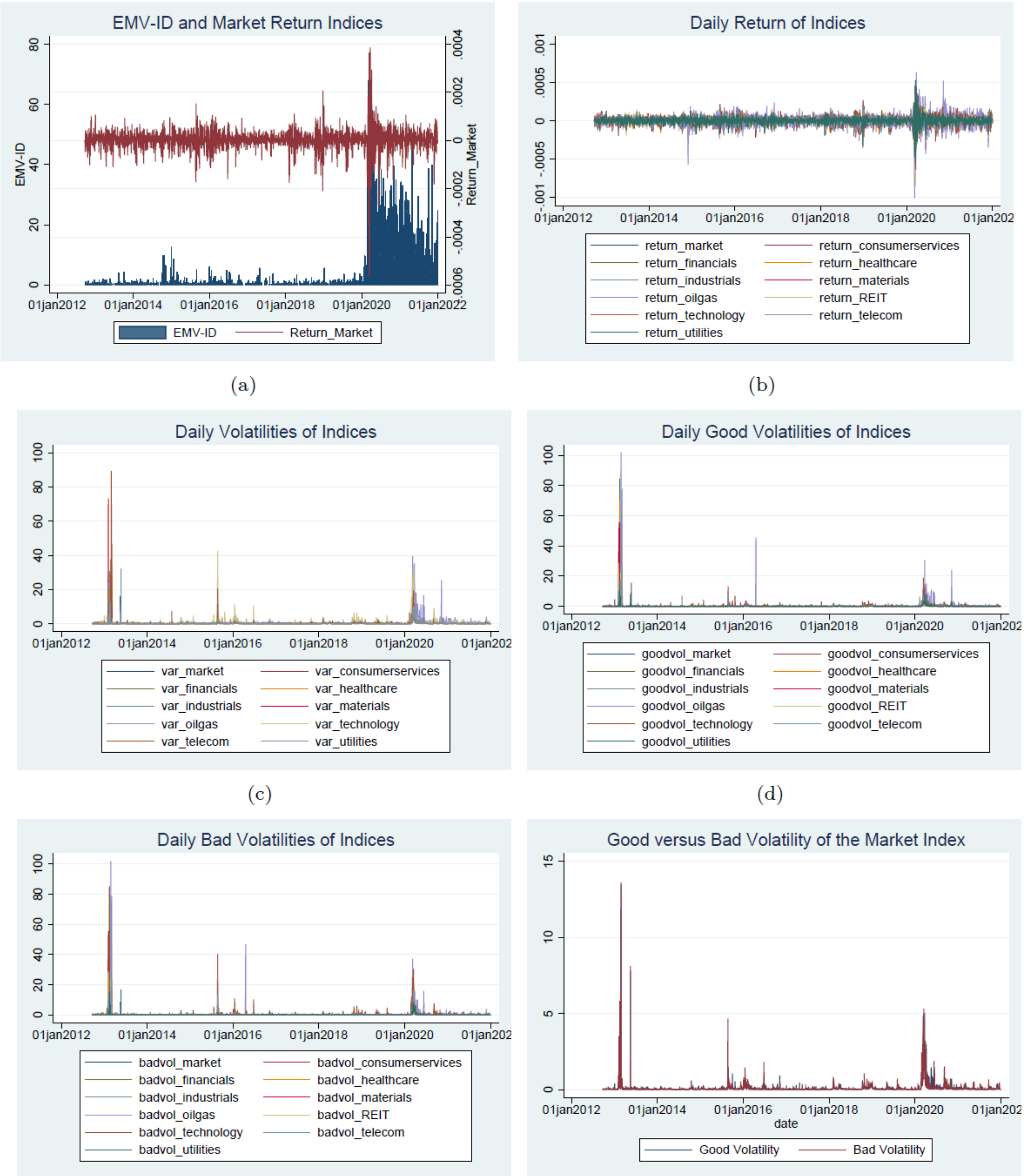
2. Data

This paper examines the time-varying effects of infectious disease equity market volatility on S&P 500 general market and sectoral indices volatility. Daily Infectious Disease Equity Market Volatility Tracker (EMV-ID) is constructed by Baker et al. (2019) to quantify the effect of infectious diseases on U.S. stock market volatility. They first specify terms in four sets: E: (economic, economy, financial), M: (stock market, equity, equities, Standard & Poor's), V: (volatility, volatile, uncertain, uncertainty, risk, risky) and ID: (epidemic, pandemic, virus, flu, disease, coronavirus, MERS, Sars, Ebola, H5N1, H1N1). Second, they count the daily number of newspaper articles containing at least one term in each category, E, M, V and I.D., representing the raw EMV-ID counts. Third, they scale the raw EMV-ID counts by the number of articles on the same day. Finally, they multiplicatively rescale these series to match the mean value of the VIX since 1985. We utilize high-frequency stock prices data (one second) of the overall USA market index and ten sectoral indices (Consumer Services, Financials, Health Care, Industrials, Materials, Oil and Gas, REIT, Technology, Telecommunication and Utilities) to construct volatility series from the Wharton Research Data Services (WRDS) from 21 September 2012 to 31 December 2021.

We apply the Wilcoxon Rank Sum Test to check the equality of the median between good and bad volatility of general market index and sectoral indices and report the findings in Table 7 in Section 4. The full sample findings indicate statistical differences in the median values in all series except Oil and Gas and Utilities. This strengthens our argument to separate the volatility into two components: good and bad volatility.

Figure 1 presents the graph of the EMV-ID index, the return series of different industries and different types of volatilities. During our sample period, five public health emergencies of international concern (PHEIC) are declared by World Health Organization (BBC, 2019; Wilder-Smith and Osman, 2020; WHO, 2016; WHO, 2019; WHO, 2020; WHO, 2022), Ebola (West African outbreak 2013–2015, outbreak in Democratic Republic of Congo 2018–2020), poliomyelitis (2014 to present), Zika (2016) and COVID-19 (2020 to present). EMV-ID index increases during these diseases, but the most significant effect is observed during the COVID-19 breakout in 2020 as presented in Figure 1.a. Figure 1.b. presents the return series of different industries. All indices experience high fluctuations during COVID-19 period, oil and gas industry experiencing the highest fluctuation. Figures 1.c, 1.d. and 1.e present the sectoral indices' volatility, good and bad volatility, respectively. Volatility increased during the 2011-2012 sovereign crisis, the oil price crash in 2016 and the breakout of COVID-19 in 2020.

Figure 1:



(a) (b) (c) (d) (e) (f)

Note: This figure reports infectious disease equity market volatility tracker index (a), daily return series (b)and three types of S&P 500 industrial volatility series: daily volatility (c), daily good volatility (d), daily bad volatility(e).

Table 1 below presents the descriptive statistics of the sectoral indices' volatility, good volatility and bad volatility for the period from 21 September 2012 to 17 January 2020 until the outbreak of COVID-19. The technology index has the highest average volatility measure, followed by the oil and gas and telecommunication indices. The telecommunication industry has the highest standard deviation in all three measures. All volatility measures have positively skewed with high kurtosis, indicating fat tails in the distributions.

Table 1: Descriptive statistics of volatility measures for the whole sample before COVID-19 outbreak.

	Index	Obs	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis	Unit Root Test
					Volatility					
Sectoral Indices	Market Index	1841	0.149	0.823	0.0583	0.00392	27.04	24.78	717.6	-40.433
	Consumer Services	1841	0.147	0.894	0.0736	0.0154	34.19	32.89	1192	-29.219
	Financials	1840	0.159	0.765	0.0762	0.00744	24.29	22.80	625.7	-34.706
	Healthcare	1839	0.227	1.346	0.106	0.0155	46.68	28.76	908.4	-41.784
	Industrials	1841	0.117	0.420	0.0647	0.00903	14.38	25.53	782.6	-30.048
	Materials	1840	0.277	1.839	0.140	0.0264	73.11	34.75	1346	-42.106
	Oil and Gas	1839	0.440	1.232	0.244	0.0364	37.69	21.02	554.0	-37.446
	REIT	1841	0.144	1.119	0.0727	0.0158	44.29	35.00	1336	-42.602
	Technology	1841	0.495	1.355	0.226	0.0224	42.46	19.24	532.5	-30.583
	Telecom	1837	0.364	2.381	0.191	0.0492	89.16	31.08	1093	-30.645
	Utilities	1842	0.188	1.112	0.104	0.0187	32.02	25.20	686.6	-38.118
					Good Volatility					
Sectoral Indices	Market Index	1841	0.0744	0.406	0.0273	0.00215	13.44	25.02	732.0	-40.574
	Consumer Services	1841	0.0736	0.447	0.0353	0.00699	17.23	33.49	1226	-29.199
	Financials	1841	0.125	2.001	0.0359	0.00412	84.36	40.72	1709	-40.519
	Healthcare	1841	0.185	2.284	0.0535	0.00721	69.84	27.38	785.9	-42.097
	Industrials	1841	0.0584	0.207	0.0295	0.00447	7.190	25.88	815.9	-29.830
	Materials	1842	0.200	2.039	0.0645	0.0130	55.62	24.70	639.0	-41.108
	Oil and Gas	1841	0.298	2.661	0.114	0.0183	101.7	33.01	1195	-42.175
	REIT	1842	0.0871	0.859	0.0345	0.00658	28.26	28.46	856.3	-42.832
	Technology	1841	0.238	0.579	0.103	0.0124	13.04	11.79	203.1	-30.977
	Telecom	1838	0.223	2.165	0.0934	0.0246	77.74	30.11	993.7	-28.034
	Utilities	1842	0.0912	0.546	0.0501	0.00801	15.46	25.13	681.7	-38.054
					Bad Volatility					
Sectoral Indices	Market Index	1841	0.0750	0.429	0.0225	0.00160	13.60	22.95	629.9	-40.643
	Consumer Services	1842	0.103	1.358	0.0318	0.00636	55.04	37.10	1468	-41.311
	Financials	1841	0.125	2.016	0.0314	0.00332	84.95	40.65	1705	-40.494
	Healthcare	1841	0.186	2.299	0.0436	0.00800	69.62	26.92	765.7	-41.728
	Industrials	1841	0.0584	0.222	0.0260	0.00376	7.191	23.00	650.8	-31.278
	Materials	1842	0.197	2.044	0.0574	0.00872	55.49	24.63	635.0	-41.131
	Oil and Gas	1841	0.302	2.678	0.109	0.0143	101.8	32.60	1169	-42.252
	REIT	1842	0.0881	0.872	0.0317	0.00577	28.46	28.26	845.8	-42.864
	Technology	1842	0.302	2.246	0.0835	0.00956	83.93	31.27	1099	-42.195
	Telecom	1838	0.226	2.185	0.0870	0.0235	78.37	29.95	986.8	-28.182
	Utilities	1842	0.0969	0.569	0.0489	0.00911	16.56	24.93	678.5	-38.199
					Infectious Disease Equity Market Volatility Index(EMV-ID)					
	EMV-ID	2,335	3.78	8.33	0	68.37	3.18	15.31	-17.48	-31.486

Note: This table reports descriptive statistics of the variables. Data is obtained from Wharton Research Data Services (WRDS) for the period from 21 September 2012 to 17 January 2020. Critical values for Dickey Fuller Unit Root Test is -3.430, -2.860 and -2.570 for 1%, 5% and 10% significance level, respectively

We examine COVID-19 period in two subgroups. Kapar et al. (2022) explore how the US sectoral and sub-sectoral indices reacted to the news of a successful development of vaccine by Pfizer and Biontech on 9 November 2020. They find out that there are considerable inter and intra sectoral variations in the impact of the vaccine news. Due to different impact of vaccine announcement on sectoral indices, we split the COVID-19 period into two sub-periods by taking 9 November 2020 as the break point: Before Vaccine and After Vaccine announcement during COVID-19 period. Although Moderna announced the first COVID-19 vaccination on 23rd January 2020, we consider Pfizer and BioNTech vaccine announcement as the breakpoint since this vaccine candidate is the first one that succeeded the first interim analysis from the Phase 3 study to fight against COVID-19.

In Section 4, Table 5 presents the descriptive statistics of the different volatility measures during the COVID-19 period before the Pfizer and Biontech vaccine announcement for the period from 20 January 2020 to 6 November 2020 and Table 6 presents the descriptive statistics of volatility measures during the COVID-19 period after the vaccine announcement for the period from 9 November 2020 to 31 December 2021. As expected, all volatility measures increased with the outbreak of COVID-19 period but significantly decreased after the vaccine announcement. The oil and gas industry index has the highest volatility, followed by technology indices before and after the Pfizer and Biontech vaccine announcement during COVID-19. The Augmented Dickey-Fuller unit root tests support the rejection of the existence of a unit root at the 1% significance level, implying that all of the volatility series and EMV-ID series are stationary.

3. Methodology

In this study, we investigate the relationship between infectious disease equity market volatility tracker and S&P 500 market index and sectoral indices different volatility measures. Initially, we calculate the realized variance, good and bad volatility following Bollerslev et al. (2019), and then we estimate the quantile regression to understand the relation between infectious disease equity market volatility tracker and different volatility measures.

Let $p_T$denote the natural logarithmic price of an arbitrary asset on day T. The price is assumed to follow the generic jump diffusion process,

$$p_T = \int_0^T \mu_\tau \, d\tau + \int_0^T \sigma_\tau dW_\tau + J_T$$

(1)

where τ and σ denote the drift and diffusive volatility processes, respectively. W is a standard Brownian motion, J is a pure jump process, and the unit time interval corresponds to a trading day. We will assume that high-frequency intraday prices p_t,p_(t+1/N),…,p_(t+1) are observed at n+1 equally spaced times over the trading day [t,t+1]. We calculate the natural logarithmic discrete-time return over the ith time-interval on day t+1 as below:

$$r_{t+i/n} = p_{t+i/n} - p_{t+(i-1)/n}$$

(2)

The daily realized variance (RV) is then simply defined by the summation of these within-day high-frequency squared returns,

$$RV_t = \sum_{i=1}^{n} r_{t-1+i/n}^2$$

(3)

As documented by Andersen et al.(2011) and Andersen et al. (2003), the realized variance converges (for n →∞) to the quadratic variation comprised of the separate components due to " continuous" and "jump" price increments,

$$RV_t = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1 \le \tau \le t} J_\tau^2$$

(4)

thus, affording increasingly more accurate ex post measures of the true latent total daily price variation for ever finer sampled intraday returns.

The realized variance measure in equation (3) does not differentiate between "good" and "bad" volatility. We decompose the total realized variation into separate components associated with the positive and negative high-frequency returns,

$$RV_t^+ = \sum_{i=1}^{n} r_{t-1+\frac{i}{n}}^2 \mathbf{1}_{[r_t - \frac{1}{n}i > 0]}$$

$$RV_t^- = \sum_{i=1}^{n} r_{t-1+\frac{i}{n}}^2 \mathbf{1}_{[r_t - \frac{1}{n}i < 0]}$$

(5)

The good and bad volatility measures obviously add up to the total daily realized variation, $RV_t = RV_t^+ + RV_t^-$

As a second step, we estimate quantile regression between volatility measures and infectious disease equity market volatility tracker. In the context of financial time series, according to Koenker and Xiao (2006) quantile regression is an ideal technique as it is robust to conditional heteroskedasticity, skewness and leptokurtosis. Therefore, we use this technique to estimate different quantile autoregressive models for each of our volatility series separately:

$$q_t(R_t|M_t) = \alpha_\tau + \beta_\tau M_t$$

(6)

where $\alpha \in (0,1)$, R_t is the any volatility series and M_t is the infectious disease equity market volatility tracker. The estimates of α_t and β_t in Equation 7 are defined as the solutions to:

$$min_{\alpha_\tau,\beta_\tau} \sum_{t=1}^{T} \rho_\tau(R_t - \alpha_\tau - \beta_\tau M_t)$$

(7)

where $\rho_\tau\ (z)$ is the check function given by $\rho_\tau\ (z) = z(\tau - \mathbf{1}_{|z\leq 0|})$, where $\mathbf{1}_{|z\leq 0|}$ is the indicator function taking only two values: 1 if $z \leq 0$ and 0 otherwise. As explained in Koenker and Hallock (2001), the function $\rho_\tau\ (z)$ imposes different weights on positive and negative residuals depending on the value of τ; when $\tau = 0.5$, his is the median estimator. We estimate the interrelationship between volatility series and infectious disease volatility tracker at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95). Thus, it provides a broader picture in helping us examine the relation.

4. Empirical Results

This study analyses the relationship between industrial uncertainty and US equity market volatility caused by infectious disease in the US from 2012 to 2021 in three sub-periods: the whole sample till COVID-19, during COVID-19 period before and after the Pfizer and Biontech vaccine announcement, respectively.

In Table 2, we analyse the transmission of volatility shocks from the US infectious equity market volatility index (EMV-ID) towards industrial volatility (IV) at different quantiles to see the differences in bearish and bullish conditions.

Table 2: Descriptive statistics of volatility measures during COVID-19 period before the Pfizer and Biontech vaccine announcement.

	Index	Obs.	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis	Unit Root Test
					Volatility					
	Market Index	204	0.708	1.190	0.248	0.0246	6.946	3.173	13.92	-5.779
Sectoral Indices	Consumer Services	204	0.870	1.899	0.265	0.0503	15.42	4.515	27.32	-5.440
	Financials	204	0.993	1.560	0.368	0.0237	9.774	2.836	12.16	-7.548
	Healthcare	204	0.640	1.212	0.205	0.0468	7.799	3.667	17.84	-5.203
	Industrials	204	0.686	1.069	0.271	0.0211	5.935	2.750	10.78	-7.533
	Materials	204	1.225	2.332	0.455	0.0582	21.50	5.111	37.43	-8.382
	Oil and Gas	204	3.560	5.860	1.193	0.119	39.45	3.080	14.56	-6.850
	REIT	204	0.898	1.451	0.275	0.0273	8.042	2.672	10.56	-6.871
	Technology	204	2.277	4.598	0.785	0.115	34.50	4.446	25.17	-6.772
	Telecom	204	1.262	2.464	0.413	0.0804	19.22	4.135	23.62	-6.137
	Utilities	204	0.981	1.839	0.298	0.0379	10.59	3.213	13.61	-5.496
					Good Volatility					
	Market Index	204	0.348	0.636	0.118	0.00884	5.025	4.014	23.31	-7.553
Sectoral Indices	Consumer Services	204	0.407	0.829	0.128	0.0233	6.301	4.234	24.44	-5.376
	Financials	204	0.515	1.014	0.146	0.0115	8.843	4.358	28.66	-9.351
	Healthcare	204	0.316	0.597	0.0959	0.0221	4.661	3.919	22.34	-6.951
	Industrials	204	0.348	0.679	0.113	0.0110	5.407	4.282	25.46	-9.635
	Materials	204	0.601	1.334	0.195	0.0275	14.44	6.716	62.05	-10.385
	Oil and Gas	204	1.804	3.410	0.505	0.0502	30.43	4.196	28.24	-8.096
	REIT	204	0.444	0.844	0.118	0.0153	6.038	3.553	18.21	-9.076
	Technology	204	1.008	1.911	0.384	0.0428	18.76	5.510	43.78	-8.200
	Telecom	204	0.587	1.056	0.203	0.0358	6.203	3.369	15.11	-6.578
	Utilities	204	0.485	0.988	0.129	0.0194	7.597	4.423	27.92	-7.491
					Bad Volatility					
	Market Index	204	0.359	0.770	0.0885	0.00884	5.300	4.135	22.34	-9.364
Sectoral Indices	Consumer Services	204	0.463	1.287	0.108	0.0214	12.54	6.259	50.24	-9.297
	Financials	204	0.477	1.017	0.123	0.0103	7.482	4.167	22.75	-11.178
	Healthcare	204	0.324	0.785	0.0867	0.0159	6.012	4.853	29.43	-8.528
	Industrials	204	0.338	0.717	0.0845	0.0102	4.331	3.902	19.18	-11.017
	Materials	204	0.624	1.718	0.155	0.0278	19.81	7.725	79.60	-12.171
	Oil and Gas	204	1.757	3.848	0.514	0.0634	36.80	5.389	41.02	-10.932
	REIT	204	0.453	1.006	0.0982	0.0112	6.553	4.039	21.07	-10.582
	Technology	204	1.269	3.533	0.290	0.0392	30.29	5.775	39.90	-10.894
	Telecom	204	0.675	1.682	0.189	0.0365	16.15	5.798	44.89	-9.081
	Utilities	204	0.496	1.164	0.114	0.0146	8.268	4.383	24.3	-8.530
					Infectious Disease Equity Market Volatility Index(EMV-ID)					
	EMV-ID	204	21.56	13.56	19.05	0	68.37	0.970	4.037	-5.542

Note: This table reports descriptive statistics of the variables during COVID-19 Period before the Pfizer and Biontech Vaccine Announcement. Data is obtained from Wharton Research Data Services (WRDS) for the period from 20 Jan 2020 to 6 November 2020. Critical values for Dickey Fuller Unit Root Test is -3.430, -2.860 and -2.570 for 1%, 5% and 10% significance level, respectively.

For example, according to the findings of total volatility, during bearish (τ = 0.05) IV conditions, the EMV-ID volatility causes a more appreciative impact on the IV of financials, oil and gas and telecom. This means that when the IV falls below the normalized region, EMV-ID puts upward pressure on the IV and may provide investment incentives for risk-taking long- term investors. However, at bullish (τ = 0.95) IV conditions, only industrials, oil and gas and technology react significantly to EMV-ID.

During the whole sample until COVID-19, EMV-ID significantly affects almost all good volatility measures irrespective of industry and quantile. However, the effect is only pronounced at high quantiles of bad volatility in some industries such as consumer services, financials, healthcare, industrials, materials, technology, telecom, and utilities. However, when the effect of magnitude is compared, the effect on bad volatilities is at a greater magnitude than on good volatilities. This means that bad volatility is much more sensitive to economic uncertainty shocks than good volatility. This could be explained with investor's behaviour. When uncertainty increases in the markets, investors tend to reduce their long positions in financial assets, decreasing prices and enhancing bad volatility (Lyu et al., 2021). Further bullish shifts in sentiment lead to downward revisions in the volatility of returns and are associated with higher future excess returns, which signifies the investor's attitude in explaining the formation of volatility (Lee et al., 2002).

Apparently, the significant impact of EMV-ID on the oil and gas industry's total, good and bad volatility is observed at all quantiles before the COVID-19. Interestingly, bad volatility of oil and gas industry is the only industry that reacts EMV-ID at all quantiles significantly compared to other industries. This indicates that oil and gas industry is the most sensitive industry to equity market volatility associated with infectious disease. Similarly, Bouri et al. (2020) also examines the predictive power of EMV-ID index for oil-market volatility and document that incorporating EMV-ID into a forecasting setting significantly improves the forecast accuracy of oil realized volatility at short-, medium-, and long-run horizons.

Overall, we have also observed that before the COVID-19 period, the relationship between EMV-ID and IV depends not only on the industrial volatility conditions but also on the good and bad volatile components and their respective conditions at lower (τ = 0.05, 0.10) and higher quantiles (τ = 0.90, 0.95). As presented in Figure 1.b., during the COVID-19 and before the vaccine announcement, uncertainty was very high in the financial markets and EMV-ID reached its highest level. Moreover, as presented in Table 2, the volatility of each industry increased significantly with the outbreak of COVID-19 as also documented by Baker et al. (2020) and Baek et al. (2020). However, once the shock has been absorbed, the total volatility exhibits a significant fall with the quick recovery of financial markets as also claimed by Basuony et al. (2021).

As seen in Table 3, the vaccine announcement mitigated the volatility in financial markets (Nguyen To et al., 2023).

Table 3: Descriptive statistics of volatility measures during COVID-19 period after the Pfizer and Biontech vaccine announcement.

	Index	Obs.	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis	Unit Root Test
					Volatility					
Sectoral Indices	Market Index	289	0.126	0.131	0.0812	0.0136	0.867	2.399	9.923	-11.636
	Consumer Services	289	0.137	0.146	0.111	0.0373	2.165	9.747	132.1	-25.078
	Financials	289	0.228	0.296	0.149	0.0392	3.437	6.231	57.76	-19.058
	Healthcare	289	0.126	0.135	0.0910	0.0239	1.799	7.348	85.18	-20.605
	Industrials	289	0.165	0.196	0.104	0.0221	2.173	4.948	42.53	-17.180
	Materials	289	0.304	0.323	0.210	0.0598	4.084	6.414	68.02	-20.845
	Oil and Gas	289	0.947	1.598	0.605	0.146	25.33	12.51	189.3	-35.725
	REIT	289	0.140	0.195	0.0983	0.0276	2.878	10.03	135.3	-25.919
	Technology	289	0.448	0.428	0.285	0.0747	2.223	1.998	6.795	-9.735
	Telecom	289	0.211	0.213	0.151	0.0473	2.407	5.235	45.52	-16.161
	Utilities	289	0.157	0.197	0.114	0.0313	2.993	10.71	151.2	-27.971
					Good Volatility					
Sectoral Indices	Market Index	289	0.126	0.131	0.0812	0.0136	0.867	2.399	9.923	-11.636
	Consumer Services	289	0.137	0.146	0.111	0.0373	2.165	9.747	132.1	-25.078
	Financials	289	0.228	0.296	0.149	0.0392	3.437	6.231	57.76	-19.058
	Healthcare	289	0.126	0.135	0.0910	0.0239	1.799	7.348	85.18	-20.605
	Industrials	289	0.165	0.196	0.104	0.0221	2.173	4.948	42.53	-17.180
	Materials	289	0.304	0.323	0.210	0.0598	4.084	6.414	68.02	-20.845
	Oil and Gas	289	0.947	1.598	0.605	0.146	25.33	12.51	189.3	-35.725
	REIT	289	0.140	0.195	0.0983	0.0276	2.878	10.03	135.3	-25.919
	Technology	289	0.448	0.428	0.285	0.0747	2.223	1.998	6.795	-9.735
	Telecom	289	0.211	0.213	0.151	0.0473	2.407	5.235	45.52	-16.161
	Utilities	289	0.157	0.197	0.114	0.0313	2.993	10.71	151.2	-27.971
					Bad Volatility					
Sectoral Indices	Market Index	289	0.0605	0.0869	0.0288	0.00559	0.657	3.420	17.33	-14.646
	Consumer Services	289	0.0663	0.0577	0.0496	0.0160	0.552	3.702	23.56	-14.276
	Financials	289	0.101	0.150	0.0569	0.0188	1.290	4.947	32.76	-16.734
	Healthcare	289	0.0581	0.0615	0.0380	0.0103	0.481	3.624	19.78	-14.708
	Industrials	289	0.0735	0.117	0.0365	0.00942	0.920	4.295	24.20	-16.493
	Materials	289	0.138	0.187	0.0771	0.0253	1.408	4.069	22.14	-16.278
	Oil and Gas	289	0.424	0.473	0.275	0.0704	3.627	3.544	18.87	-16.016
	REIT	289	0.0616	0.0748	0.0386	0.0120	0.748	5.037	37.65	-15.971
	Technology	289	0.223	0.283	0.116	0.0306	1.788	2.917	12.77	-12.790
	Telecom	289	0.105	0.120	0.0661	0.0222	1.288	4.841	38.77	-13.239
	Utilities	289	0.0697	0.0551	0.0545	0.0161	0.444	2.963	15.51	-12.536
					Infectious Disease Equity Market Volatility Index (EMV-ID)					
	EMV-ID	289	12.63	7.36	11.61	0	47.59	1.19	5.28	-11.399

Note: This table reports descriptive statistics of the variables during COVID-19 Period after the Pfizer and Biontech Vaccine Announcement. Data is obtained from Wharton Research Data Services (WRDS) for the period from 9 November 2020 to 31 December 2021. Critical values for Dickey Fuller Unit Root Test is -3.430, -2.860 and -2.570 for 1%, 5% and 10% significance level, respectively.

Grab et al. (2021) and Kapar et al. (2022) analyse the effect of vaccine announcements on the stock return of different industries. They suggest that the stock market sectors hit hardest by the pandemic benefited the most from positive vaccine news. When we analyse the effect of vaccine announcement on the volatility in Table 6, except bearish conditions of consumer services, financials, health care, industrials, real estate and utilities and bullish conditions of financials, health care, materials, real estate, all other industrial volatilities are affected from EMV-ID. In terms of the magnitude, the impact of EMV-ID on good or bad volatility depends on the industry. In financials, health care and materials, the impact is more pronounced on good components. In contrast, in consumer services, industrials, real estate, telecom and utilities, the impact is more noticeable in bad components. The findings of the Wilcoxon Rank Sum Test in Table 7 also indicate that there are no statistical differences between good and bad volatility of consumer services, oil and gas, telecom and utilities industries on the reaction for EMV-ID at the median level.

Table 4 presents the results for the entire sample until the COVID-19 outbreak.

Table 4: The Relation between industry volatilities and infectious disease equity market volatility index for the whole sample before COVID-19 outbreak.

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
	Total Volatility											
Sectoral Indices	Market Index	0.0003	0.0012*	0.0017**	0.0018*	0.0044***	0.0061***	0.0075***	0.0110***	0.0218***	0.0485***	0.0561*
	Consumer Services	0.0003	0.0000	0.0010	0.0021**	0.0017	0.0021	0.0048**	0.0059*	0.0085*	0.0351***	0.0325*
	Financials	-0.0015**	0.0011	0.0016*	0.0012	0.0012	0.0022	0.0049*	0.0072**	0.0093*	0.0310**	0.0147
	Health Care	0.0012	0.0027**	0.0049***	0.0053***	0.0087***	0.0091***	0.0109***	0.0119**	0.0373***	0.0503***	0.0633
	Industrials	0.0010	0.0012*	0.0018**	0.0025**	0.0029**	0.0042**	0.0044*	0.0107***	0.0174***	0.0318***	0.0393**
	Materials	0.0023*	0.0015	0.0015	0.0055***	0.0083***	0.0140***	0.0137***	0.0227***	0.0289***	0.0535***	0.0317
	Oil and Gas	0.0060***	0.0136***	0.0170***	0.0189***	0.0335***	0.0523***	0.0603***	0.0817***	0.1103***	0.2194***	0.3917***
	REIT	-0.0009	0.0006	0.0012	0.0005	0.0009	0.0013	0.0006	0.0052*	0.0059	0.0059	0.0021
	Technology	0.0004	0.0030	0.0034	0.0050	0.0105**	0.0136**	0.0191*	0.0377***	0.0764***	0.1662***	0.2968**
	Telecom	0.0035**	0.0030	0.0014	-0.0001	-0.0010	0.0005	-0.0016	0.0037	0.0129	0.0482**	0.0501
	Utilities	-0.0003	0.0003	0.0016	0.0006	0.0030	0.0050**	0.0058**	0.0099***	0.0127***	0.0135	0.0281
	Good Volatility											
Sectoral Indices	Market Index	0.0003***	0.0004***	0.0006***	0.0009***	0.0012***	0.0018***	0.0026***	0.0036***	0.0052***	0.0059***	0.0090***
	Consumer Services	0.0003***	0.0003***	0.0005***	0.0007***	0.0009***	0.0014***	0.0020***	0.0025***	0.0039***	0.0051***	0.0055***
	Financials	0.0002***	0.0005***	0.0007***	0.0010***	0.0012***	0.0015***	0.0024***	0.0036***	0.0045***	0.0069***	0.0082***
	Health Care	0.0002**	0.0005***	0.0009***	0.0013***	0.0016***	0.0019***	0.0025***	0.0043***	0.0049***	0.0056***	0.0086***
	Industrials	0.0003***	0.0003***	0.0006***	0.0007***	0.0009***	0.0015***	0.0018***	0.0025***	0.0036***	0.0050***	0.0067***
	Materials	0.0006***	0.0009***	0.0013***	0.0019***	0.0024***	0.0030***	0.0037***	0.0045***	0.0064***	0.0096***	0.0107***
	Oil and Gas	0.0026***	0.0029***	0.0047***	0.0065***	0.0079***	0.0100***	0.0119***	0.0164***	0.0201***	0.0271***	0.0782***
	REIT	0.0001**	0.0002***	0.0004***	0.0005***	0.0006***	0.0009***	0.0011***	0.0016***	0.0031***	0.0038***	0.0065***
	Technology	0.0006***	0.0007***	0.0013***	0.0016***	0.0028***	0.0040***	0.0063***	0.0107***	0.0158***	0.0226***	0.0282***
	Telecom	0.0002	0.0004***	0.0009***	0.0013***	0.0017***	0.0021***	0.0024***	0.0035***	0.0046***	0.0063***	0.0048
	Utilities	0.0004***	0.0004***	0.0007***	0.0010***	0.0015***	0.0016***	0.0017***	0.0018***	0.0023***	0.0024***	0.0017
	Bad Volatility											
Sectoral Indices	Market Index	-0.0001	0.0001	0.0004	0.0008**	0.0011*	0.0021***	0.0061***	0.0070***	0.0184***	0.0377***	0.0480**
	Consumer Services	0.0005	0.0002	0.0004	0.0002	0.0018***	0.0030***	0.0041***	0.0046**	0.0094***	0.0206***	0.0252*
	Financials	-0.0001	-0.0002	-0.0005	-0.0001	-0.0002	0.0017*	0.0029**	0.0083***	0.0107***	0.0232***	0.0327**
	Health Care	0.0001	0.0006	0.0008	0.0026***	0.0035***	0.0047***	0.0095***	0.0132***	0.0308***	0.0591***	0.0932***
	Industrials	0.0004	0.0004*	0.0003	0.0005	0.0007	0.0019**	0.0045***	0.0048***	0.0079***	0.0239***	0.0280**
	Materials	0.0011*	0.0014**	0.0012*	0.0010	0.0024**	0.0022	0.0074***	0.0084**	0.0131**	0.0335***	0.0235
	Oil and Gas	0.0042***	0.0052***	0.0101***	0.0101***	0.0110***	0.0239***	0.0292***	0.0605***	0.0699***	0.1582***	0.1378***
	REIT	-0.0002	0.0001	0.0003	0.0000	0.0002	0.0002	0.0012	0.0002	-0.0023	0.0087*	0.0059
	Technology	-0.0017*	-0.0005	0.0004	0.0041***	0.0040**	0.0037	0.0061	0.0180**	0.0560***	0.1461***	0.2620***
	Telecom	-0.0002	0.0010	0.0010	0.0008	0.0024**	0.0023	0.0049**	0.0075**	0.0086*	0.0293**	0.0444
	Utilities	0.0001	0.0001	-0.0000	0.0019***	0.0016*	0.0015	0.0013	0.0043**	0.0091***	0.0217***	0.0180*

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 21 September 2012 to 17 January 2020. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Tables 5 and 6 present the results for the COVID-19 period before and after the Pfizer and Biontech vaccine announcement, respectively. The first part of Tables 4, 5 and 6 demonstrates how the US equity market volatility index (EMVI) affects the overall industrial volatility (IV) at different quantiles.

According to Table 5, during this period, the appreciative impact of EMV-ID is significant for all industries, irrespective of the quantile condition and volatility measures.

Table 5: **The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period before Pfizer and Biontech vaccine announcement.**

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market	0.0035***	0.0049***	0.0065***	0.0122***	0.0158***	0.0223***	0.0347***	0.0411***	0.0596***	0.0831***	0.1004***
	Consumer Services	0.0023***	0.0033***	0.0068***	0.0108***	0.0142***	0.0190***	0.0375***	0.0591***	0.0769***	0.0949***	0.1430**
	Financials	0.0041***	0.0064***	0.0135***	0.0178***	0.0238***	0.0320***	0.0537***	0.0617***	0.0754***	0.1317***	0.1554***
	Health Care	0.0016**	0.0033***	0.0055***	0.0089***	0.0112***	0.0181***	0.0263***	0.0417***	0.0552***	0.0646***	0.1005***
	Industrials	0.0027***	0.0046***	0.0100***	0.0126***	0.0150***	0.0264***	0.0317***	0.0376***	0.0438***	0.0958***	0.1032***
	Materials	0.0052***	0.0073***	0.0143***	0.0220***	0.0301***	0.0356***	0.0493***	0.0687***	0.0712***	0.1422***	0.1713***
	OIl and Gas	0.0138***	0.0217***	0.0348***	0.0512***	0.0867***	0.1628***	0.1916***	0.2387***	0.3146***	0.4237***	0.4932***
	REIT	0.0039***	0.0055***	0.0123***	0.0148***	0.0241***	0.0353***	0.0527***	0.0572***	0.0713***	0.1161***	0.1356***
	Technology	0.0078***	0.0101***	0.0146***	0.0236***	0.0304***	0.0459***	0.0767***	0.1109***	0.1384***	0.2539***	0.4382***
	Telecom	0.0013	0.0061***	0.0114***	0.0163***	0.0237***	0.0417***	0.0525***	0.0692***	0.0960***	0.1443***	0.1610**
	Utilities	0.0033***	0.0051***	0.0099***	0.0137***	0.0178***	0.0324***	0.0516***	0.0755***	0.0863***	0.1097***	0.1837***
							Good Volatility					
Sectoral Indices	Market	0.0012***	0.0014***	0.0027***	0.0037***	0.0066***	0.0121***	0.0161***	0.0255***	0.0299***	0.0391***	0.0898***
	Consumer Services	0.0006**	0.0014***	0.0027***	0.0045***	0.0075***	0.0100***	0.0123***	0.0219***	0.0533***	0.0624***	0.1229***
	Financials	0.0021***	0.0038***	0.0051***	0.0081***	0.0126***	0.0178***	0.0283***	0.0357***	0.0476***	0.0693***	0.0935***
	Health Care	0.0012***	0.0017***	0.0031***	0.0041***	0.0047***	0.0073***	0.0147***	0.0222***	0.0338***	0.0481***	0.0774***
	Industries	0.0013***	0.0022***	0.0028***	0.0050***	0.0063***	0.0151***	0.0182***	0.0230***	0.0333***	0.0446***	0.0537***
	Materials	0.0014***	0.0029***	0.0056***	0.0062***	0.0104***	0.0192***	0.0264***	0.0370***	0.0455***	0.0627***	0.1256***
	Oil and Gas	0.0086***	0.0118***	0.0227***	0.0362***	0.0489***	0.0836***	0.1152***	0.1555***	0.1847***	0.2146***	0.3724***
	REIT	0.0011***	0.0027***	0.0039***	0.0052***	0.0065***	0.0171***	0.0237***	0.0320***	0.0453***	0.0584***	0.0830***
	Technology	0.0027***	0.0039***	0.0055***	0.0067***	0.0090***	0.0162***	0.0324***	0.0505***	0.0693***	0.1183***	0.2075***
	Telecom	0.0004	0.0022***	0.0054***	0.0091***	0.0094***	0.0157***	0.0223***	0.0372***	0.0629***	0.0699***	0.1202***
	Utilities	0.0013***	0.0016***	0.0040***	0.0046***	0.0086***	0.0135***	0.0288***	0.0362***	0.0469***	0.0809***	0.0732***
							Bad Volatility					
Sectoral Indices	Market	0.0009***	0.0014***	0.0027***	0.0038***	0.0056***	0.0075***	0.0128***	0.0199***	0.0251***	0.0447**	0.0842***
	Consumer Services	0.0009***	0.0013***	0.0023***	0.0041***	0.0059***	0.0072***	0.0148***	0.0265***	0.0345***	0.0593***	0.0985**
	Financials	0.0020***	0.0026***	0.0039***	0.0056***	0.0073***	0.0121***	0.0183***	0.0221***	0.0299***	0.0566***	0.0844***
	Health Care	0.0005**	0.0012***	0.0021***	0.0032***	0.0046***	0.0071***	0.0104***	0.0169***	0.0215***	0.0389**	0.0905***
	Industrials	0.0011***	0.0014***	0.0021***	0.0034***	0.0048***	0.0068***	0.0120***	0.0149***	0.0215***	0.0328**	0.0723***
	Materials	0.0014***	0.0025***	0.0042***	0.0055***	0.0071***	0.0115***	0.0196***	0.0242***	0.0370***	0.0682**	0.1104**
	Oil and Gas	0.0079***	0.0103***	0.0203***	0.0260***	0.0333***	0.0493***	0.0602***	0.0915***	0.1251***	0.2096***	0.3016***
	REIT	0.0014***	0.0021***	0.0033***	0.0045***	0.0058***	0.0124***	0.0160***	0.0244***	0.0315***	0.0567**	0.0957***
	Technology	0.0027***	0.0041***	0.0064***	0.0081***	0.0128***	0.0186***	0.0312***	0.0461***	0.0677***	0.1253	0.3642***
	Telecom	0.0014***	0.0021***	0.0058***	0.0089***	0.0118***	0.0173***	0.0210***	0.0360***	0.0468***	0.0751***	0.1194***
	Utilities	0.0015***	0.0023***	0.0034***	0.0049***	0.0064***	0.0100***	0.0210***	0.0276***	0.0388***	0.0530***	0.0854**

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 20 January 2020 to 6 November December 2020 to see the relation during COVID-19 period before the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 6: **The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period after the Pfizer and Biontech vaccine announcement.**

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market	0.0002	0.0005**	0.0011***	0.0020***	0.0030***	0.0033***	0.0039***	0.0045***	0.0062***	0.0084*	0.0124**
	Consumer Services	0.0005	0.0009***	0.0020***	0.0024***	0.0030***	0.0030***	0.0033***	0.0042***	0.0051***	0.0074**	0.0074*
	Financials	0.0006	0.0013**	0.0018***	0.0028***	0.0031***	0.0044***	0.0048***	0.0073***	0.0087***	0.0114	0.0177
	Health Care	0.0001	0.0008**	0.0009**	0.0009**	0.0012**	0.0015**	0.0013*	0.0018*	0.0042**	0.0054*	0.0061
	Industrials	0.0005	0.0007**	0.0017***	0.0023***	0.0026***	0.0042***	0.0054***	0.0073***	0.0097***	0.0128**	0.0165*
	Materials	0.0013**	0.0019**	0.0023**	0.0029***	0.0035***	0.0060***	0.0053**	0.0056*	0.0149***	0.0155**	0.0127
	OIl and Gas	0.0049**	0.0044*	0.0054	0.0150***	0.0132***	0.0256***	0.0292***	0.0380***	0.0467***	0.0667***	0.1015***
	REIT	0.0002	0.0005*	0.0011***	0.0017***	0.0020***	0.0019***	0.0024***	0.0032***	0.0051**	0.0079**	0.0082
	Technology	0.0025***	0.0027***	0.0033***	0.0054***	0.0073***	0.0091***	0.0094***	0.0136***	0.0252***	0.0358***	0.0390***
	Telecom	0.0010*	0.0006	0.0007	0.0019***	0.0024***	0.0026***	0.0026**	0.0039**	0.0043	0.0097*	0.0151*
	Utilities	0.0006	0.0004	0.0018***	0.0027***	0.0030***	0.0034***	0.0042***	0.0043***	0.0080***	0.0090***	0.0179***
							Good Volatility					
Sectoral Indices	Market	-0.0001	0.0001	0.0005***	0.0004**	0.0004	0.0007*	0.0015***	0.0026***	0.0047***	0.0062***	0.0087**
	Consumer Services	-0.0001	0.0001	0.0002	0.0004*	0.0008***	0.0010***	0.0013***	0.0022***	0.0023***	0.0043***	0.0030
	Financials	0.0002	0.0003	0.0004*	0.0010***	0.0017***	0.0020***	0.0021***	0.0030***	0.0055***	0.0127***	0.0206
	Health Care	-0.0001	0.0002	0.0006***	0.0005***	0.0006***	0.0007***	0.0012***	0.0020***	0.0022***	0.0038**	0.0054
	Industrials	0.0001	0.0002	0.0006***	0.0006***	0.0007**	0.0007*	0.0017***	0.0022**	0.0044***	0.0100***	0.0099
	Materials	0.0006***	0.0006***	0.0011***	0.0012***	0.0013**	0.0026***	0.0042***	0.0048***	0.0101***	0.0171***	0.0139
	Oil and Gas	0.0010	0.0012	0.0026**	0.0032**	0.0098***	0.0123***	0.0133***	0.0222***	0.0260***	0.0548***	0.0450
	REIT	0.0000	0.0002	0.0003**	0.0005***	0.0008***	0.0007**	0.0014***	0.0028***	0.0034***	0.0071***	0.0065
	Technology	0.0002	0.0001	0.0004	0.0014**	0.0009	0.0013	0.0050***	0.0064***	0.0093***	0.0182***	0.0164*
	Telecom	0.0005**	0.0006***	0.0005***	0.0007**	0.0013***	0.0017***	0.0021***	0.0030***	0.0041***	0.0077***	0.0058
	Utilities	-0.0000	-0.0000	0.0003*	0.0007***	0.0007***	0.0009***	0.0016***	0.0027***	0.0045***	0.0049**	0.0158**
							Bad Volatility					
Sectoral Indices	Market	0.0002	0.0003***	0.0002**	0.0006***	0.0008***	0.0009***	0.0018***	0.0030***	0.0046***	0.0067***	0.0057
	Consumer Services	0.0002	0.0003**	0.0005**	0.0009***	0.0011***	0.0012***	0.0018***	0.0021***	0.0030***	0.0027	0.0060
	Financials	0.0000	0.0000	0.0001	0.0005**	0.0005	0.0006	0.0020***	0.0028***	0.0045***	0.0099***	0.0104
	Health Care	0.0002	0.0002*	0.0003*	0.0005**	0.0006***	0.0006**	0.0010***	0.0021***	0.0027***	0.0034	0.0068*
	Industrials	0.0002**	0.0003***	0.0005***	0.0006***	0.0006**	0.0011***	0.0023***	0.0036***	0.0053***	0.0055**	0.0075
	Materials	0.0002	0.0005**	0.0007***	0.0010***	0.0013***	0.0022***	0.0039***	0.0051***	0.0061***	0.0068	0.0201
	Oil and Gas	0.0002	0.0002	0.0021	0.0037***	0.0058***	0.0072***	0.0114***	0.0162***	0.0285***	0.0538***	0.0388
	REIT	0.0001	0.0002	0.0005***	0.0006***	0.0009***	0.0014***	0.0017***	0.0023***	0.0021***	0.0037*	0.0053
	Technology	0.0003	0.0009***	0.0012***	0.0020***	0.0023***	0.0032***	0.0038**	0.0075**	0.0178***	0.0185**	0.0192
	Telecom	0.0005***	0.0006***	0.0005**	0.0007***	0.0011***	0.0020***	0.0023***	0.0043***	0.0038**	0.0054	0.0041
	Utilities	0.0002	0.0003	0.0005***	0.0011***	0.0012***	0.0013***	0.0021***	0.0028***	0.0037***	0.0034***	0.0040

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 9 November December 2020 to 31 December 2021 to see the relation during COVID-19 period after the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

As the findings of the Wilcoxon Rank Sum Test suggest in Table 7, there are statistical differences in the median values of good and bad volatility in all indices except the Oil and Gas and Utilities sectors. Due to this statistical difference, we demonstrate the results by decomposing volatility into good and bad components in the second and third parts of Tables 4, 5 and 6.

Table 7: Wilcoxon Rank Sum Test

		Whole Sample until COVID-19		During COVID-19 before the vaccine announcement		During COVID-19 after the vaccine announcement		Whole Sample	
		z value	Probability	z value	Probability	z value	Probability	z value	Probability
Sectoral Indices	Market Index	5.463	0.0000	1.816	0.0693	3.597	0.0003	6.087	0.0000
	Consumer Services	3.749	0.0002	1.122	0.2620	0.588	0.5565	3.546	0.0004
	Financials	3.710	0.0002	0.767	0.4433	2.754	0.0059	3.774	0.0002
	Health Care	5.509	0.0000	1.259	0.2079	2.577	0.0100	5.994	0.0000
	Industrials	4.080	0.0000	1.580	0.1141	4.059	0.0000	4.949	0.0000
	Materials	3.391	0.0007	1.820	0.0687	3.750	0.0002	4.362	0.0000
	Oil and Gas	1.918	0.0551	-0.023	0.9819	1.473	0.1407	1.525	0.1273
	REIT	3.639	0.0003	0.974	0.3301	3.197	0.0014	4.182	0.0000
	Technology	5.318	0.0000	1.898	0.0577	2.530	0.0114	5.563	0.0000
	Telecom	2.236	0.0254	0.768	0.4423	1.406	0.1597	2.553	0.0107
	Utilities	0.416	0.6771	0.544	0.5864	1.509	0.1314	0.937	0.3486

Note: Wilcoxon Rank Sum Test is applied to check the equality of the medians of the two samples (good volatility versus bad volatility).

Hence, we empirically verify that economic uncertainty shocks can significantly and persistently increase industrial volatility during COVID-19 until the vaccine announcement. Bad volatility is associated with declines in prices, and good volatility is associated with increases in prices. After the outbreak of COVID-19, economic uncertainty shocks initially caused an increase in bad volatility due to significant price decreases with the outbreak of COVID-19. However, once the shock has been absorbed, the stock market recovers with big price jumps and good volatility increases, as presented in Figure 1.f. The findings of the Wilcoxon Rank Sum Test in Table 7 also support this inference. During the COVID-19 period before the vaccine announcement, there is no statistical difference between good and bad volatility in their reaction to a change in the EMV-ID index. As price decreases with the shocks followed by a recovery, we observe that both good and bad volatility of industry indices are affected by infectious disease economic uncertainty. Hence, during COVID-19 period, all volatility measures are affected from uncertainty irrespective of the quantile condition.

To conclude, according to Tables 2, 3 and 4, it is evident that the positive transmission of volatile shocks from the EMV-ID towards the IV strengthens and gains momentum as the IV volatility transits from bearish (lower quantiles) towards the bullish (higher quantiles) condition irrespective of the period considered. Interestingly, during the COVID-19 period before the vaccine announcement and bearish IV conditions, the appreciative impact of EMV-ID is more significant for all industries compared with the other periods. This is supported by Kundu and Paul (2022), who examine the effect of economic policy uncertainty on stock market volatility for the seven countries in differential market conditions such as bull and bear markets. The estimation results suggest that the impact of EPU is significant in the bear market. Finally, the magnitudes of the effect of EMV-ID uncertainty on industrial volatility across the three subsample periods are significantly different from each other, indicating that the effects of economic uncertainty shocks on industrial volatilities vary significantly under different macroeconomic conditions as documented by Lyu et al. (2021) for the oil market.

5. Robustness Analysis

To investigate the sensitivity of our findings, we also estimate the quantile regression with bootstrapped standard errors (Tables 8, 9 and 10) and robust standard errors (Tables 11, 12 and 13) as a robustness check. Our results are robust to different estimation types and indicate a similar relation between U.S. industrial volatility resulting from infectious disease and different industrial volatility measures.

Table 8: The Relation between industry volatilities and infectious disease equity market volatility index for the whole sample before COVID-19 outbreak.

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market Index	0.0003	0.0012*	0.0017**	0.0018	0.0044**	0.0061*	0.0075	0.0110*	0.0216**	0.0475**	0.0446*
	Consumer Services	0.0003	0.0000	0.0010	0.0021	0.0017	0.0021	0.0048	0.0059	0.0085	0.0356***	0.0325
	Financials	-0.0015	0.0011	0.0014	0.0017	0.0012	0.0022	0.0049	0.0083*	0.0092**	0.0309**	0.0146
	Health Care	0.0010	0.0026	0.0049***	0.0053***	0.0087***	0.0090***	0.0109*	0.0115	0.0372**	0.0485	0.0626***
	Industrials	0.0010	0.0012	0.0018**	0.0025	0.0029	0.0042**	0.0044	0.0106	0.0174**	0.0318**	0.0393
	Materials	0.0020	0.0015	0.0014	0.0055	0.0083**	0.0140***	0.0137**	0.0226**	0.0287*	0.0534**	0.0311
	Oil and Gas	0.0060	0.0134***	0.0170***	0.0189***	0.0335**	0.0523***	0.0603***	0.0817***	0.1103***	0.2194**	0.3917***
	REIT	-0.0009	0.0006	0.0012	0.0005	0.0009	0.0013	0.0006	0.0052	0.0060*	0.0059	0.0021
	Technology	0.0004	0.0030	0.0034	0.0050	0.0105	0.0136	0.0191	0.0377	0.0764**	0.1662	0.3004
	Telecom	0.0035	0.0030***	0.0014	-0.0001	-0.0010	0.0006	-0.0016	0.0037	0.0129	0.0482*	0.0493
	Utilities	-0.0003	0.0003	0.0016	0.0006	0.0030	0.0050***	0.0058**	0.0099**	0.0127**	0.0135	0.0281*
							Good Volatility					
Sectoral Indices	Market Index	0.0003***	0.0004***	0.0006***	0.0009***	0.0012***	0.0018***	0.0026***	0.0036***	0.0052***	0.0059***	0.0089***
	Consumer Services	0.0003***	0.0003***	0.0005***	0.0007***	0.0009***	0.0014***	0.0020***	0.0025***	0.0039***	0.0051***	0.0055***
	Financials	0.0002	0.0005***	0.0007***	0.0010***	0.0012***	0.0015***	0.0024***	0.0036***	0.0045***	0.0069***	0.0082***
	Health Care	0.0002*	0.0005***	0.0009***	0.0013***	0.0016***	0.0019***	0.0025***	0.0043***	0.0049***	0.0056***	0.0085***
	Industrials	0.0003***	0.0003***	0.0006***	0.0007***	0.0009***	0.0015***	0.0018***	0.0025***	0.0036***	0.0050***	0.0067***
	Materials	0.0006***	0.0009***	0.0013***	0.0019***	0.0024***	0.0030***	0.0037***	0.0045***	0.0064***	0.0096***	0.0107***
	Oil and Gas	0.0026***	0.0029***	0.0047***	0.0065***	0.0079***	0.0100***	0.0119***	0.0164***	0.0201***	0.0271***	0.0782
	REIT	0.0001*	0.0002	0.0004***	0.0005***	0.0006***	0.0009***	0.0011***	0.0016***	0.0031***	0.0038***	0.0065*
	Technology	0.0006**	0.0007***	0.0013***	0.0016***	0.0028***	0.0040***	0.0063***	0.0107***	0.0158***	0.0226***	0.0282*
	Telecom	0.0002	0.0004**	0.0009***	0.0013***	0.0017***	0.0021***	0.0024***	0.0035***	0.0046***	0.0063***	0.0048
	Utilities	0.0004***	0.0004***	0.0007***	0.0010***	0.0015***	0.0016***	0.0017***	0.0018***	0.0023***	0.0024***	0.0017
							Bad Volatility					
Sectoral Indices	Market Index	-0.0001	0.0001	0.0004	0.0008	0.0011	0.0021	0.0061***	0.0070	0.0183***	0.0376**	0.0478
	Consumer Services	0.0005**	0.0002	0.0004	0.0002	0.0018	0.0030**	0.0041**	0.0046	0.0094*	0.0206***	0.0252
	Financials	-0.0001	-0.0002	-0.0005	-0.0001	-0.0001	0.0017	0.0029	0.0083***	0.0107	0.0233***	0.0327*
	Health Care	0.0001	0.0006*	0.0008	0.0026**	0.0035***	0.0047**	0.0095**	0.0132**	0.0308***	0.0590***	0.0890**
	Industrials	0.0004	0.0004	0.0003	0.0005	0.0007	0.0019	0.0043*	0.0048*	0.0079	0.0239**	0.0280
	Materials	0.0011	0.0014***	0.0012***	0.0010	0.0024**	0.0022	0.0074*	0.0084**	0.0131	0.0335**	0.0235
	Oil and Gas	0.0042*	0.0052**	0.0101***	0.0101***	0.0114**	0.0239***	0.0292**	0.0605***	0.0699***	0.1582***	0.1378*
	REIT	-0.0002	0.0001	0.0003	0.0000	0.0002	0.0002	0.0012	0.0002	-0.0023	0.0087	0.0059
	Technology	-0.0005	0.0004	0.0041	0.0040	0.0037	0.0061	0.0180*	0.0560	0.1461*	0.2620***	
	Telecom	-0.0002	0.0010**	0.0011	0.0008	0.0025*	0.0023	0.0049*	0.0075	0.0090	0.0293	0.0447**
	Utilities	0.0001	0.0001	-0.0000	0.0019	0.0016*	0.0015	0.0013	0.0043	0.0091	0.0217***	0.0180**

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) with bootstrapped standard errors during the sample period from 21 September 2012 to 17 January 2020. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 9: **The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period before the Pfizer and Biontech vaccine announcement.**

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market	0.0035**	0.0049***	0.0065***	0.0122***	0.0158***	0.0223***	0.0347***	0.0411***	0.0596***	0.0831***	0.1004***
	Consumer Services	0.0023***	0.0033***	0.0068***	0.0108**	0.0142***	0.0190**	0.0375**	0.0591***	0.0769***	0.0949***	0.1430***
	Financials	0.0041**	0.0064***	0.0135***	0.0178***	0.0238***	0.0320**	0.0537***	0.0617***	0.0754***	0.1317***	0.1554***
	Health Care	0.0016	0.0033***	0.0055***	0.0089***	0.0112***	0.0181***	0.0263***	0.0417***	0.0552***	0.0646***	0.1005***
	Industrials	0.0027*	0.0046***	0.0100***	0.0126***	0.0150***	0.0264***	0.0317***	0.0376***	0.0438***	0.0958***	0.1032***
	Materials	0.0052***	0.0073***	0.0143***	0.0220***	0.0301***	0.0356***	0.0493***	0.0687***	0.0712***	0.1422***	0.1713***
	OIl and Gas	0.0138**	0.0217***	0.0348***	0.0512*	0.0867***	0.1628***	0.1916***	0.2387***	0.3146***	0.4237***	0.4932***
	REIT	0.0039***	0.0055***	0.0123***	0.0148***	0.0241***	0.0353***	0.0527***	0.0572***	0.0713***	0.1161***	0.1356***
	Technology	0.0078***	0.0101***	0.0146***	0.0236***	0.0304***	0.0459***	0.0767***	0.1109***	0.1384***	0.2539***	0.4382***
	Telecom	0.0013	0.0061*	0.0114***	0.0163**	0.0237**	0.0417***	0.0525***	0.0692***	0.0960***	0.1443***	0.1610***
	Utilities	0.0033***	0.0051***	0.0099***	0.0137***	0.0178*	0.0324**	0.0516***	0.0755***	0.0863***	0.1097***	0.1837***
							Good Volatility					
Sectoral Indices	Market	0.0012***	0.0014**	0.0027***	0.0037*	0.0066**	0.0121***	0.0161***	0.0255***	0.0299***	0.0391**	0.0898***
	Consumer Services	0.0006	0.0014	0.0027***	0.0045***	0.0075***	0.0100***	0.0123	0.0219	0.0533***	0.0624**	0.1229***
	Financials	0.0021***	0.0038***	0.0051***	0.0081***	0.0126***	0.0178***	0.0283***	0.0357***	0.0476***	0.0693**	0.0935**
	Health Care	0.0012***	0.0017***	0.0031***	0.0041***	0.0047***	0.0073*	0.0147***	0.0222***	0.0338***	0.0481**	0.0774***
	Industries	0.0013*	0.0022***	0.0028***	0.0050***	0.0063***	0.0151***	0.0182***	0.0230***	0.0333***	0.0446**	0.0537*
	Materials	0.0014***	0.0029*	0.0056***	0.0062***	0.0104**	0.0192***	0.0264***	0.0370***	0.0455***	0.0627	0.1256
	Oil and Gas	0.0086**	0.0118**	0.0227***	0.0362***	0.0489***	0.0836***	0.1152***	0.1555***	0.1847***	0.2146***	0.3724***
	REIT	0.0011	0.0027***	0.0039***	0.0052***	0.0065*	0.0171***	0.0237***	0.0320***	0.0453***	0.0584***	0.0830***
	Technology	0.0027*	0.0039***	0.0055***	0.0067**	0.0090***	0.0162	0.0324**	0.0505***	0.0693***	0.1183**	0.2075**
	Telecom	0.0004	0.0022**	0.0054**	0.0091***	0.0094**	0.0157***	0.0223**	0.0372***	0.0629***	0.0699***	0.1202***
	Utilities	0.0013***	0.0016	0.0040***	0.0046***	0.0086***	0.0135***	0.0288***	0.0362***	0.0469***	0.0809***	0.0732
							Bad Volatility					
Sectoral Indices	Market	0.0009**	0.0014***	0.0027***	0.0038***	0.0056***	0.0075***	0.0128***	0.0199***	0.0251***	0.0447***	0.0842***
	Consumer Services	0.0009***	0.0013***	0.0023**	0.0041***	0.0059***	0.0072	0.0148**	0.0265***	0.0345***	0.0593***	0.0985***
	Financials	0.0020***	0.0026***	0.0039***	0.0056***	0.0073***	0.0121***	0.0183***	0.0221***	0.0299***	0.0566***	0.0844***
	Health Care	0.0005	0.0012***	0.0021***	0.0032***	0.0046***	0.0071**	0.0104**	0.0169***	0.0215***	0.0389**	0.0905***
	Industrials	0.0011***	0.0014***	0.0021***	0.0034***	0.0048***	0.0068***	0.0120***	0.0149***	0.0215***	0.0328**	0.0723***
	Materials	0.0014**	0.0025***	0.0042***	0.0055***	0.0071	0.0115***	0.0196***	0.0242***	0.0370***	0.0682***	0.1104
	Oil and Gas	0.0079***	0.0103***	0.0203***	0.0260***	0.0333***	0.0493***	0.0602***	0.0915***	0.1251***	0.2096***	0.3016**
	REIT	0.0014***	0.0021***	0.0033***	0.0045***	0.0058***	0.0124***	0.0160***	0.0244***	0.0315***	0.0567***	0.0957***
	Technology	0.0027***	0.0041***	0.0064***	0.0081***	0.0128***	0.0186***	0.0312***	0.0461***	0.0677***	0.1253**	0.3642***
	Telecom	0.0014	0.0021	0.0058***	0.0089***	0.0118***	0.0173***	0.0210**	0.0360***	0.0468***	0.0751***	0.1194***
	Utilities	0.0015***	0.0023***	0.0034***	0.0049***	0.0064***	0.0100***	0.0210***	0.0276***	0.0388***	0.0530***	0.0854**

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) with bootstrapped standard errors during the sample period from 20 January 2020 to 6 November December 2020 to see the relation during COVID-19 period before the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 10: **The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period after the Pfizer and Biontech vaccine announcement.**

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market	0.0035***	0.0049***	0.0065***	0.0122***	0.0158***	0.0223***	0.0347***	0.0411***	0.0596***	0.0831***	0.1004***
	Consumer Services	0.0023***	0.0033***	0.0068***	0.0108***	0.0142***	0.0190***	0.0375***	0.0591***	0.0769***	0.0949***	0.1430**
	Financials	0.0041***	0.0064***	0.0135***	0.0178***	0.0238***	0.0320***	0.0537***	0.0617***	0.0754***	0.1317***	0.1554***
	Health Care	0.0016**	0.0033***	0.0055***	0.0089***	0.0112***	0.0181***	0.0263***	0.0417***	0.0552***	0.0646***	0.1005***
	Industrials	0.0027***	0.0046***	0.0100***	0.0126***	0.0150***	0.0264***	0.0317***	0.0376***	0.0438***	0.0958***	0.1032***
	Materials	0.0052***	0.0073***	0.0143***	0.0220***	0.0301***	0.0356***	0.0493***	0.0687***	0.0712***	0.1422***	0.1713***
	OIl and Gas	0.0138***	0.0217***	0.0348***	0.0512***	0.0867***	0.1628***	0.1916***	0.2387***	0.3146***	0.4237***	0.4932***
	REIT	0.0039***	0.0055***	0.0123***	0.0148***	0.0241***	0.0353***	0.0527***	0.0572***	0.0713***	0.1161***	0.1356***
	Technology	0.0078***	0.0101***	0.0146***	0.0236***	0.0304***	0.0459***	0.0767***	0.1109***	0.1384***	0.2539***	0.4382***
	Telecom	0.0013	0.0061***	0.0114***	0.0163***	0.0237***	0.0417***	0.0525***	0.0692***	0.0960***	0.1443***	0.1610**
	Utilities	0.0033***	0.0051***	0.0099***	0.0137***	0.0178***	0.0324***	0.0516***	0.0755***	0.0863***	0.1097***	0.1837***
							Good Volatility					
Sectoral Indices	Market	0.0012***	0.0014***	0.0027***	0.0037***	0.0066***	0.0121***	0.0161***	0.0255***	0.0299***	0.0391***	0.0898***
	Consumer Services	0.0006**	0.0014***	0.0027***	0.0045***	0.0075***	0.0100***	0.0123***	0.0219***	0.0533***	0.0624***	0.1229***
	Financials	0.0021***	0.0038***	0.0051***	0.0081***	0.0126***	0.0178***	0.0283***	0.0357***	0.0476***	0.0693***	0.0935***
	Health Care	0.0012***	0.0017***	0.0031***	0.0041***	0.0047***	0.0073***	0.0147***	0.0222***	0.0338***	0.0481***	0.0774***
	Industries	0.0013***	0.0022***	0.0028***	0.0050***	0.0063***	0.0151***	0.0182***	0.0230***	0.0333***	0.0446***	0.0537***
	Materials	0.0014***	0.0029***	0.0056***	0.0062***	0.0104***	0.0192***	0.0264***	0.0370***	0.0455***	0.0627***	0.1256***
	Oil and Gas	0.0086***	0.0118***	0.0227***	0.0362***	0.0489***	0.0836***	0.1152***	0.1555***	0.1847***	0.2146***	0.3724***
	REIT	0.0011***	0.0027***	0.0039***	0.0052***	0.0065***	0.0171***	0.0237***	0.0320***	0.0453***	0.0584***	0.0830***
	Technology	0.0027***	0.0039***	0.0055***	0.0067***	0.0090***	0.0162***	0.0324***	0.0505***	0.0693***	0.1183***	0.2075***
	Telecom	0.0004	0.0022***	0.0054***	0.0091***	0.0094***	0.0157***	0.0223***	0.0372***	0.0629***	0.0699***	0.1202***
	Utilities	0.0013***	0.0016***	0.0040***	0.0046***	0.0086***	0.0135***	0.0288***	0.0362***	0.0469***	0.0809***	0.0732***
							Bad Volatility					
Sectoral Indices	Market	0.0009***	0.0014***	0.0027***	0.0038***	0.0056***	0.0075***	0.0128***	0.0199***	0.0251***	0.0447**	0.0842***
	Consumer Services	0.0009***	0.0013***	0.0023***	0.0041***	0.0059***	0.0072***	0.0148***	0.0265***	0.0345***	0.0593***	0.0985**
	Financials	0.0020***	0.0026***	0.0039***	0.0056***	0.0073***	0.0121***	0.0183***	0.0221***	0.0299***	0.0566***	0.0844***
	Health Care	0.0005**	0.0012***	0.0021***	0.0032***	0.0046***	0.0071***	0.0104***	0.0169***	0.0215***	0.0389**	0.0905***
	Industrials	0.0011***	0.0014***	0.0021***	0.0034***	0.0048***	0.0068***	0.0120***	0.0149***	0.0215***	0.0328**	0.0723***
	Materials	0.0014***	0.0025***	0.0042***	0.0055***	0.0071***	0.0115***	0.0196***	0.0242***	0.0370***	0.0682**	0.1104**
	Oil and Gas	0.0079***	0.0103***	0.0203***	0.0260***	0.0333***	0.0493***	0.0602***	0.0915***	0.1251***	0.2096***	0.3016***
	REIT	0.0014***	0.0021***	0.0033***	0.0045***	0.0058***	0.0124***	0.0160***	0.0244***	0.0315***	0.0567**	0.0957***
	Technology	0.0027***	0.0041***	0.0064***	0.0081***	0.0128***	0.0186***	0.0312***	0.0461***	0.0677***	0.1253	0.3642***
	Telecom	0.0014***	0.0021***	0.0058***	0.0089***	0.0118***	0.0173***	0.0210***	0.0360***	0.0468***	0.0751***	0.1194***
	Utilities	0.0015***	0.0023***	0.0034***	0.0049***	0.0064***	0.0100***	0.0210***	0.0276***	0.0388***	0.0530***	0.0854**

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) with bootstrapped standard errors during the sample period from 9 November December 2020 to 31 December 2021 to see the relation during COVID-19 period after the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 11: The Relation between industry volatilities and infectious disease equity market volatility index for the whole sample before COVID-19 outbreak.

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
							Total Volatility					
Sectoral Indices	Market Index	0.0003	0.0012	0.0017*	0.0018	0.0044**	0.0061***	0.0075	0.0110***	0.0216***	0.0475	0.0446***
	Consumer Services	0.0003	0.0000	0.0010	0.0021	0.0017	0.0021	0.0048	0.0059	0.0085	0.0356***	0.0325***
	Financials	-0.0015	0.0011	0.0014	0.0017	0.0012	0.0022	0.0049	0.0083**	0.0092	0.0309***	0.0146***
	Health Care	0.0010	0.0026	0.0049***	0.0053***	0.0087**	0.0090***	0.0109***	0.0115	0.0372***	0.0485	0.0626***
	Industrials	0.0010	0.0012	0.0018*	0.0025	0.0029	0.0042*	0.0044	0.0106*	0.0174***	0.0318***	0.0393
	Materials	0.0020*	0.0015	0.0014	0.0055	0.0083**	0.0140**	0.0137**	0.0226***	0.0287***	0.0534***	0.0311***
	Oil and Gas	0.0060	0.0134**	0.0170***	0.0189***	0.0335*	0.0523***	0.0603**	0.0817*	0.1103***	0.2194**	0.3917
	REIT	-0.0009	0.0006	0.0012	0.0005	0.0009	0.0013	0.0006	0.0052**	0.0060*	0.0059	0.0021
	Technology	0.0004	0.0030	0.0034	0.0050	0.0105	0.0136*	0.0191	0.0377	0.0764	0.1662	0.3004***
	Telecom	0.0035***	0.0030**	0.0014	-0.0001	-0.0010	0.0006	-0.0016	0.0037	0.0129*	0.0482***	0.0493***
	Utilities	-0.0003	0.0003	0.0016	0.0006	0.0030	0.0050**	0.0058**	0.0099*	0.0127***	0.0135	0.0281***
							Good Volatility					
Sectoral Indices	Market Index	0.0003***	0.0004***	0.0006***	0.0009***	0.0012***	0.0018***	0.0026***	0.0036***	0.0052***	0.0059***	0.0089***
	Consumer Services	0.0003***	0.0003***	0.0005***	0.0007***	0.0009***	0.0014***	0.0020***	0.0025***	0.0039***	0.0051***	0.0055*
	Financials	0.0002*	0.0005***	0.0007***	0.0010***	0.0012***	0.0015***	0.0024***	0.0036***	0.0045***	0.0069***	0.0082**
	Health Care	0.0002*	0.0005***	0.0009***	0.0013***	0.0016***	0.0019***	0.0025***	0.0043***	0.0049***	0.0056***	0.0085***
	Industrials	0.0003***	0.0003***	0.0006***	0.0007***	0.0009***	0.0015***	0.0018***	0.0025***	0.0036***	0.0050***	0.0067***
	Materials	0.0006***	0.0009***	0.0013***	0.0019***	0.0024***	0.0030***	0.0037***	0.0045***	0.0064***	0.0096***	0.0107***
	Oil and Gas	0.0026***	0.0029***	0.0047***	0.0065***	0.0079***	0.0100***	0.0119***	0.0164***	0.0201***	0.0271***	0.0782***
	REIT	0.0001	0.0002*	0.0004***	0.0005***	0.0006***	0.0009***	0.0011***	0.0016***	0.0031***	0.0038***	0.0065***
	Technology	0.0006***	0.0007**	0.0013***	0.0016***	0.0028***	0.0040***	0.0063***	0.0107***	0.0158***	0.0226***	0.0282***
	Telecom	0.0002	0.0004*	0.0009***	0.0013***	0.0017***	0.0021***	0.0024***	0.0035***	0.0046***	0.0063***	0.0048***
	Utilities	0.0004**	0.0004***	0.0007***	0.0010***	0.0015***	0.0016***	0.0017***	0.0018***	0.0023***	0.0024***	0.0017***
							Bad Volatility					
Sectoral Indices	Market Index	-0.0001	0.0001	0.0004	0.0008	0.0011	0.0021	0.0061*	0.0070***	0.0183***	0.0376***	0.0478***
	Consumer Services	0.0005	0.0002	0.0004	0.0002	0.0018	0.0030***	0.0041	0.0046**	0.0094**	0.0206***	0.0252
	Financials	-0.0001	-0.0002	-0.0005	-0.0001	-0.0001	0.0017	0.0029	0.0083***	0.0107***	0.0233***	0.0327
	Health Care	0.0001	0.0006	0.0008	0.0026**	0.0035**	0.0047**	0.0095	0.0132***	0.0308***	0.0590***	0.0890**
	Industrials	0.0004*	0.0004*	0.0003	0.0005	0.0007	0.0019	0.0043	0.0048***	0.0079	0.0239***	0.0280**
	Materials	0.0011	0.0014***	0.0012**	0.0010	0.0024**	0.0022	0.0074	0.0084*	0.0131***	0.0335***	0.0235***
	Oil and Gas	0.0042**	0.0052*	0.0101***	0.0101***	0.0114***	0.0239**	0.0292***	0.0605***	0.0699	0.1582***	0.1378***
	REIT	-0.0002	0.0001	0.0003	0.0000	0.0002	0.0002	0.0012	0.0002	-0.0023**	0.0087	0.0059***
	Technology	-0.0017	-0.0005	0.0004	0.0041**	0.0040**	0.0037	0.0061	0.0180	0.0560	0.1461**	0.2620***
	Telecom	-0.0002	0.0010	0.0011	0.0008	0.0025*	0.0023	0.0049	0.0075*	0.0090	0.0293	0.0447***
	Utilities	0.0001	0.0001	-0.0000	0.0019***	0.0016**	0.0015**	0.0013	0.0043*	0.0091*	0.0217***	0.0180***

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 21 September 2012 to 17 January 2020. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 12: The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period before the Pfizer and Biontech vaccine announcement.

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
	Total Volatility											
Sectoral Indices	Market	0.0035***	0.0049***	0.0065***	0.0122***	0.0158***	0.0223***	0.0347***	0.0411***	0.0596***	0.0831***	0.1004***
	Consumer Services	0.0023*	0.0033***	0.0068***	0.0108***	0.0142***	0.0190***	0.0375**	0.0591***	0.0769***	0.0949***	0.1430***
	Financials	0.0041**	0.0064***	0.0135***	0.0178***	0.0238***	0.0320***	0.0537***	0.0617***	0.0754***	0.1317***	0.1554***
	Health Care	0.0016	0.0033***	0.0055***	0.0089***	0.0112***	0.0181***	0.0263***	0.0417***	0.0552***	0.0646***	0.1005***
	Industrials	0.0027*	0.0046***	0.0100***	0.0126***	0.0150***	0.0264***	0.0317***	0.0376***	0.0438***	0.0958***	0.1032***
	Materials	0.0052**	0.0073***	0.0143***	0.0220***	0.0301***	0.0356***	0.0493***	0.0687***	0.0712***	0.1422***	0.1713***
	Oil and Gas	0.0138**	0.0217***	0.0348***	0.0512***	0.0867***	0.1628***	0.1916***	0.2387***	0.3146***	0.4237***	0.4932***
	REIT	0.0039**	0.0055***	0.0123***	0.0148***	0.0241***	0.0353***	0.0527***	0.0572***	0.0713***	0.1161***	0.1356***
	Technology	0.0078**	0.0101***	0.0146***	0.0236***	0.0304***	0.0459**	0.0767***	0.1109***	0.1384***	0.2539***	0.4382***
	Telecom	0.0013	0.0061***	0.0114***	0.0163***	0.0237***	0.0417***	0.0525***	0.0692***	0.0960***	0.1443***	0.1610***
	Utilities	0.0033**	0.0051***	0.0099***	0.0137***	0.0178***	0.0324***	0.0516***	0.0755***	0.0863***	0.1097***	0.1837***
	Good Volatility											
Sectoral Indices	Market	0.0012	0.0014	0.0027***	0.0037***	0.0066	0.0121***	0.0161***	0.0255***	0.0299***	0.0391***	0.0898***
	Consumer Services	0.0006	0.0014	0.0027***	0.0045**	0.0075***	0.0100***	0.0123**	0.0219**	0.0533***	0.0624***	0.1229**
	Financials	0.0021**	0.0038***	0.0051***	0.0081***	0.0126***	0.0178***	0.0283***	0.0357***	0.0476***	0.0693***	0.0935**
	Health Care	0.0012*	0.0017**	0.0031***	0.0041***	0.0047***	0.0073***	0.0147***	0.0222***	0.0338***	0.0481**	0.0774***
	Industries	0.0013	0.0022***	0.0028***	0.0050***	0.0063***	0.0151***	0.0182***	0.0230***	0.0333***	0.0446*	0.0537***
	Materials	0.0014	0.0029*	0.0056***	0.0062***	0.0104	0.0192***	0.0264***	0.0370***	0.0455***	0.0627***	0.1256***
	Oil and Gas	0.0086***	0.0118***	0.0227***	0.0362***	0.0489***	0.0836***	0.1152***	0.1555***	0.1847***	0.2146***	0.3724**
	REIT	0.0011	0.0027***	0.0039***	0.0052***	0.0065***	0.0171***	0.0237*	0.0320***	0.0453***	0.0584***	0.0830
	Technology	0.0027	0.0039**	0.0055***	0.0067***	0.0090**	0.0162**	0.0324*	0.0505***	0.0693***	0.1183	0.2075***
	Telecom	0.0004	0.0022*	0.0054	0.0091***	0.0094***	0.0157***	0.0223***	0.0372***	0.0629***	0.0699***	0.1202***
	Utilities	0.0013*	0.0016	0.0040***	0.0046***	0.0086***	0.0135***	0.0288***	0.0362***	0.0469***	0.0809***	0.0732***
	Bad Volatility											
Sectoral Indices	Market	0.0009*	0.0014***	0.0027***	0.0038***	0.0056***	0.0075***	0.0128***	0.0199***	0.0251***	0.0447**	0.0842***
	Consumer Services	0.0009*	0.0013**	0.0023***	0.0041***	0.0059***	0.0072***	0.0148***	0.0265***	0.0345***	0.0593***	0.0985***
	Financials	0.0020***	0.0026***	0.0039***	0.0056***	0.0073***	0.0121***	0.0183***	0.0221***	0.0299***	0.0566***	0.0844***
	Health Care	0.0005	0.0012***	0.0021***	0.0032***	0.0046***	0.0071**	0.0104***	0.0169***	0.0215***	0.0389***	0.0905***
	Industrials	0.0011***	0.0014***	0.0021***	0.0034***	0.0048***	0.0068***	0.0120***	0.0149***	0.0215***	0.0328***	0.0723***
	Materials	0.0014*	0.0025***	0.0042***	0.0055***	0.0071***	0.0115***	0.0196***	0.0242***	0.0370***	0.0682***	0.1104
	Oil and Gas	0.0079***	0.0103***	0.0203***	0.0260***	0.0333***	0.0493***	0.0602***	0.0915***	0.1251***	0.2096***	0.3016***
	REIT	0.0014**	0.0021***	0.0033***	0.0045***	0.0058***	0.0124***	0.0160***	0.0244***	0.0315***	0.0567***	0.0957***
	Technology	0.0027*	0.0041***	0.0064***	0.0081***	0.0128***	0.0186***	0.0312***	0.0461***	0.0677***	0.1253***	0.3642***
	Telecom	0.0014	0.0021**	0.0058***	0.0089***	0.0118***	0.0173***	0.0210***	0.0360**	0.0468***	0.0751***	0.1194***
	Utilities	0.0015***	0.0023***	0.0034***	0.0049***	0.0064***	0.0100***	0.0210***	0.0276***	0.0388***	0.0530***	0.0854***

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 20 January 2020 to 6 November December 2020 to see the relation during COVID-19 period before the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

Table 13: The Relation between industry volatilities and infectious disease equity market volatility index during the COVID-19 period after the Pfizer and Biontech vaccine announcement.

	Quantiles	(0.05)	(0.10)	(0.20)	(0.30)	(0.40)	(0.50)	(0.60)	(0.70)	(0.80)	(0.90)	(0.95)
	Total Volatility											
Sectoral Indices	Market	0.0002	0.0005*	0.0011**	0.0020**	0.0030***	0.0033***	0.0039	0.0045***	0.0062***	0.0084***	0.0124*
	Consumer Services	0.0005	0.0009	0.0020***	0.0024***	0.0030***	0.0030***	0.0033***	0.0042***	0.0051***	0.0074***	0.0074**
	Financials	0.0006	0.0013*	0.0018*	0.0028***	0.0031**	0.0044***	0.0048***	0.0073***	0.0087**	0.0114*	0.0177
	Health Care	0.0001	0.0008***	0.0009**	0.0009**	0.0012*	0.0015**	0.0013*	0.0018	0.0042***	0.0054***	0.0061**
	Industrials	0.0005	0.0007	0.0017**	0.0023***	0.0026***	0.0042***	0.0054***	0.0073***	0.0097***	0.0128***	0.0165***
	Materials	0.0013	0.0019*	0.0023**	0.0029**	0.0035**	0.0060***	0.0053***	0.0056	0.0149***	0.0155	0.0127***
	Oil and Gas	0.0049**	0.0044*	0.0054	0.0150***	0.0132**	0.0256***	0.0292***	0.0380***	0.0467***	0.0667***	0.1015***
	REIT	0.0002	0.0005	0.0011*	0.0017***	0.0020***	0.0019***	0.0024**	0.0032**	0.0051***	0.0079**	0.0082***
	Technology	0.0025***	0.0027***	0.0033**	0.0054*	0.0073**	0.0091***	0.0094**	0.0136**	0.0252***	0.0358**	0.0390***
	Telecom	0.0010*	0.0006	0.0007	0.0019	0.0024**	0.0026**	0.0026**	0.0039*	0.0043**	0.0097	0.0151**
	Utilities	0.0006	0.0004	0.0018***	0.0027***	0.0030***	0.0034***	0.0042***	0.0043***	0.0080***	0.0090***	0.0179***
	Good Volatility											
Sectoral Indices	Market	-0.0001	0.0001	0.0005**	0.0004*	0.0004	0.0007	0.0015	0.0026	0.0047***	0.0062***	0.0087***
	Consumer Services	-0.0001	0.0001	0.0002	0.0004	0.0008*	0.0010***	0.0013	0.0022***	0.0023***	0.0043***	0.0030***
	Financials	0.0002	0.0003	0.0004	0.0010	0.0017***	0.0020***	0.0021***	0.0030	0.0055	0.0127***	0.0206***
	Health Care	-0.0001	0.0002	0.0006**	0.0005**	0.0006**	0.0007*	0.0012	0.0020*	0.0022***	0.0038	0.0054***
	Industrials	0.0001	0.0002	0.0006**	0.0006***	0.0007**	0.0007*	0.0017***	0.0022	0.0044*	0.0100***	0.0099
	Materials	0.0006	0.0006	0.0011**	0.0012**	0.0013*	0.0026**	0.0042***	0.0048*	0.0101***	0.0171***	0.0139***
	Oil and Gas	0.0010	0.0012	0.0026*	0.0032	0.0098***	0.0123***	0.0133***	0.0222***	0.0260***	0.0548***	0.0450***
	REIT	0.0000	0.0002	0.0003	0.0005*	0.0008**	0.0007*	0.0014	0.0028	0.0034***	0.0071***	0.0065***
	Technology	0.0002	0.0001	0.0004	0.0014	0.0009	0.0013	0.0050**	0.0064***	0.0093***	0.0182***	0.0164***
	Telecom	0.0005	0.0006***	0.0005*	0.0007*	0.0013**	0.0017**	0.0021*	0.0030***	0.0041***	0.0077***	0.0058***
	Utilities	-0.0000	-0.0000	0.0003	0.0007**	0.0007**	0.0009*	0.0016**	0.0027***	0.0045***	0.0049***	0.0158**
	Bad Volatility											
Sectoral Indices	Market	0.0002	0.0003**	0.0002	0.0006*	0.0008***	0.0009***	0.0018**	0.0030***	0.0046**	0.0067***	0.0057*
	Consumer Services	0.0002	0.0003**	0.0005**	0.0009**	0.0011***	0.0012***	0.0018***	0.0021***	0.0030***	0.0027**	0.0060***
	Financials	0.0000	0.0000	0.0001	0.0005	0.0005	0.0006	0.0020**	0.0028***	0.0045***	0.0099**	0.0104**
	Health Care	0.0002*	0.0002	0.0003	0.0005*	0.0006**	0.0006**	0.0010	0.0021***	0.0027***	0.0034***	0.0068*
	Industrials	0.0002	0.0003*	0.0005***	0.0006***	0.0006***	0.0011*	0.0023***	0.0036***	0.0053***	0.0055***	0.0075***
	Materials	0.0002	0.0005*	0.0007*	0.0010***	0.0013***	0.0022**	0.0039***	0.0051***	0.0061***	0.0068**	0.0201
	Oil and Gas	0.0002	0.0002	0.0021	0.0037*	0.0058***	0.0072***	0.0114***	0.0162***	0.0285***	0.0538***	0.0388**
	REIT	0.0001	0.0002	0.0005***	0.0006***	0.0009***	0.0014***	0.0017***	0.0023***	0.0021***	0.0037**	0.0053*
	Technology	0.0003	0.0009*	0.0012**	0.0020**	0.0023***	0.0032***	0.0038	0.0075*	0.0178***	0.0185***	0.0192
	Telecom	0.0005**	0.0006***	0.0005**	0.0007**	0.0011*	0.0020***	0.0023***	0.0043***	0.0038**	0.0054**	0.0041
	Utilities	0.0002	0.0003**	0.0005	0.0011***	0.0012***	0.0013***	0.0021***	0.0028***	0.0037***	0.0034***	0.0040***

*Note: This table reports the estimates by regressing industrial total, good and bad volatility on infectious disease equity market volatility index (EMV-ID) using a quantile regression model at different quantiles (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95) during the sample period from 9 November December 2020 to 31 December 2021 to see the relation during COVID-19 period after the Pfizer and Biontech vaccine announcement. *, **, *** represents significancy at the 10%, 5% and 1% levels, respectively.*

6. Conclusion

The current study delves deeper into understanding the asymmetric impact of infectious diseases on industrial sectors in the US. Employing the Infectious Disease Equity Market Volatility Index (EMV- ID) constructed by Baker et al. (2020), we investigate the effect of equity market volatility due to infectious disease on industrial volatility from 2012 to 2021. We use ten industrial sector indices (i.e., consumer services, financials, health care, industrials, materials, oil and gas, real estate, technology, telecommunication, and utilities) and decompose industry volatility into good and bad components to examine how these components vary in response to equity market volatility index at different quantiles in sub-periods before COVID-19, during COVID-19 before and after the Pfizer and Biontech vaccine announcement.

The results show that the transmission of volatile shocks from the stock market strongly enhances the bad components of industrial volatility before the outbreak of COVID-19 and both components of industrial volatility during COVID-19 before the vaccine announcement. The positive transmission of volatile shocks from the EMV-ID towards industrial volatility enhances as industrial volatility transits from bearish to bullish conditions, irrespective of the period considered. We conclude that the relationship between infectious disease equity market volatility and industrial volatility depends on the good and bad volatile components and their respective conditions at different quantiles during different time frames.

Our findings have several important implications for investors, risk managers and regulators. Firstly, our paper suggests that the EMV-ID uncertainty shocks on good and bad volatility depend on the sector and the distribution. Investors and risk managers should consider the infectious economic uncertainty index as a risk factor and incorporate the EMV-ID index into a forecasting setting of the realized volatility of industries, especially in forecasting the realized volatility of the oil and gas industry. EMV-ID index should also guide investors in constructing a market timing strategy. Regulators can implement prudent policies to reduce economic uncertainty and prevent the volatility spillover between sectors, thereby maintaining the stability of all financial systems and the economy. As a future work, we believe the same analysis should be applied to stock markets of other regions to reveal the effect of uncertainty on the stock market volatility.

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PERFORMANCE AND TRACKING EFFICIENCY OF COMMODITY ETFS IN THE UK

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Abstract

This paper examines the performance and tracking efficiency of twenty eight iShares ETFs traded on the London Stock Exchange in the UK. The results indicate that, on average, the performance of the examined ETFs has been positive during their entire trading history. However, these ETFs have failed to fully replicate the performance of the underlying commodities and indexes. At the cumulative level, an average underperformance of 320 basis points is found. In addition, at the sample level, about 52% of daily tracking errors are negative (indicating underperformance), and 47% of tracking errors are positive (reflecting outperformance). Based on our results, the tracking error is induced by the departure from the full replication of the underlying assets. In addition, tracking error is found to be positively related to the age of ETFs but negatively to their assets. It is also found that ETFs applying physical replication have relatively lower tracking errors than ETFs pursuing synthetic replication. Finally, no significant differences are found in tracking errors among the managing companies of commodity ETFs.

Keywords: ETFs, commodities, performance, tracking error

1. Introduction

This study focuses on Exchange Traded Funds (ETFs) which invest in commodities. Investors use commodities tools to diversify their portfolios. In addition, during highly volatile equity markets, investing in commodities can act as a relatively safe haven, even though commodities themselves are not risk-free investments. The prices of commodities are affected by several factors, such as unusual weather conditions, natural disasters, unsuitable agricultural techniques, pollution, human activity, political and economic crises, and war conflicts.

Publicly traded commodities include metals, energy, livestock, meat and agricultural products. Access to commodity markets is attained in several ways including the physical purchase of a commodity, as well as investing in futures contracts, options and commodity ETFs. A commodity ETF invests in agricultural products, natural resources and metals. The key benefits of commodity ETFs concern the potential for high portfolio diversification, low cost, variety of assets, continuous trading, high liquidity and tax efficiency.

Commodity ETFs attain exposure to the desired commodities either by physically storing the selected commodity, or via investing in futures contracts. The latter is the most commonly adopted option among commodity ETFs and has the benefit of avoiding the storage costs regarding the physical exposure. However, this "futures-based" approach is subject to the "rolling costs" relating to rolling the expiring futures contracts by closing them out and reopening them as future dated ones. Finally, several ETFs choose to get access to commodities by tracking relevant commodity indexes.

The performance of commodity ETFs can be affected by several factors. The difference between the spot and future prices of the underlying commodities is one of these factors. Money market (collateral) yield and the rolling yield also affect ETFs' performance. Money market yield is the revenue gained via investing the underlying assets of a commodity ETF in interest bearing accounts, including Treasury Bills or Treasury Inflation-Protected Securities (TIPS). Rolling yield refers to the gains and losses from rolling the expiring futures contracts. Developments in equity markets can also bear an impact on the performance of commodity ETFs.

The performance of commodity ETFs has been evaluated by several studies. Sousa (2014) shows that metal ETFs traded on the NYSE Arca have negative but statistically insignificant alphas, while their tracking error is low. Neff and Isengildina-Massa (2018) also find that the average tracking error of commodity ETFs is small even though, occasionally, tracking errors can be quite large. Rompotis (2016) reveals that the physically backed commodity ETFs perform better than their futures-based peers. He also finds that the tracking error of futures-based ETFs is significantly higher than that of the physically backed ETFs. Similar results are reported by Fassas (2014). On the UK-listed equity ETFs, by investigating the tracking performance of physical and synthetic ETFs during the period 2008-2013, Mateus and Rahmani (2015) find no significant differences in their ability to replicate the performance of their benchmarks. Similar results are provided by Maurer and Williams (2015). Merz (2015) investigates the tracking risk of physical and synthetic European ETFs and provides evidence that ETFs that follow a synthetic replication strategy, rather than holding the underlying securities comprising the benchmark, are less prone to tracking error. However, in most cases, they underperform both the benchmarks and their physical counterparts.

Furthermore, Perera et al. (2022) note that the replication method, along with the volatility in the prices of the underlying commodities, can affect the tracking ability of agricultural ETFs. They also show that the tracking error of these ETFs is not trivial, but it does not last very long. Stewart et al. (2023) show that the tracking error of commodity ETFs and Exchange Traded Notes (ETNs) focusing on the agricultural and energy sectors is driven by the arbitrage process inherent to these products. The authors also report no material differences in the tracking ability across agricultural and energy ETFs. Guo and Leung (2015) show that the leveraged commodity ETFs underperform their benchmarks in the long run. Similar results are reported by Murphy and Wright (2010). In this respect, Guedj et al. (2011) note that it is not easy for futures-based commodity ETFs to replicate their benchmarks in the long run because the term structure of futures contracts may lead to large deviations between the price of ETFs and the spot price of the underlying commodities.

In this paper, we examine the performance and tracking efficiency of twenty eight ETFs that are traded on the London Stock Exchange (LSE). These ETFs are the so-called "iShares", which are managed by BlackRock. To the best of our knowledge, this is the first study on the commodity ETFs listed in the UK. The results show that the examined ETFs fail to fully replicate the performance of the underlying commodities and indexes. The average cumulative underperformance equals 320 basis points (bps). Underperformance is also verified by the fact that the number of days with negative raw tracking errors is on average higher than the number of days with positive raw tracking errors.

2. Data and Methodology

2.1 Data and Descriptive Statistics

The sample of our study includes twenty eight commodity iShares traded on the LSE.[1] Table 1 presents the profiles of these ETFs. Twenty ETFs are physically exposed to precious metals, including gold, silver, platinum and palladium. Three futures-based ETFs track relevant commodity indexes, while five synthetic ETFs invest in commodities including cotton, copper, coffee, sugar and crude oil. The oldest ETF in the sample is about 19.8 years old, while the newest one is just 1.5 years old. Moreover, the largest ETF is the Invesco Physical Gold ETC, whose assets on 31 December 2023 amounted to $14.2 billion. The average ETF in the sample held $2 billion on the same date. Finally, the average expense ratio of the examined ETFs is 0.30%, with minimum and maximum expense ratios being equal to 0.11% and 0.49%, respectively. Table 1 also reports the managing company of each ETF in the sample. One ETF is provided by HANETF. Four ETFs are managed by DWS. Invesco offers three ETFs. Nine ETFs (iShares) are provided by BlackRock. Finally, Wisdom Tree adds eleven ETFs to our sample.

Table 1: Profiles of ETFs

Symbol	Name	Benchmark	Provider	Replication	Inception Date	Age[1]	Assets ($M)[1]	Expense Ratio
RMAU	The Royal Mint Responsibly Sourced Physical Gold ETC	Gold Spot	HANETF	Physical	14/2/2020	3.88	692.89	0.25
XGLD	Xtrackers Physical Gold ETC	Gold Spot	DWS	Physical	15/6/2010	13.55	1,920.00	0.25
XGDU	Xtrackers IE Physical Gold ETC Securities	Gold Spot	DWS	Physical	22/4/2020	3.69	3,070.00	0.11
XPPT	Xtrackers IE Physical Platinum ETC Securities	Platinum	DWS	Physical	16/4/2020	3.71	14.28	0.38
XSLR	Xtrackers IE Physical Silver ETC Securities	Silver	DWS	Physical	29/4/2020	3.67	104.93	0.20
SGLD	Invesco Physical Gold ETC	Gold Spot	INVESCO	Physical	24/6/2009	14.53	14,200.00	0.12
SPPT	Invesco Physical Platinum ETC	Platinum	INVESCO	Physical	15/4/2011	12.72	21.02	0.19
SSLV	Invesco Physical Silver ETC	Silver	INVESCO	Physical	15/4/2011	12.72	161.60	0.19
IGLN	iShares Physical Gold ETC	Gold Spot	ISHARES	Physical	8/4/2011	12.74	13,050.00	0.12
IGLG	iShares Physical Gold GBP Hedged ETC	Gold Spot	ISHARES	Physical	5/7/2022	1.49	11.53	0.25
IPDM	iShares Physical Palladium ETC	Palladium	ISHARES	Physical	8/4/2011	12.74	15.61	0.20
IPLT	iShares Physical Platinum ETC	Platinum	ISHARES	Physical	8/4/2011	12.74	70.55	0.20
ISLN	iShares Physical Silver ETC	Silver	ISHARES	Physical	8/4/2011	12.74	515.09	0.20
ICOM	iShares Diversified Commodity Swap UCITS ETF	Bloomberg Commodity TRI	ISHARES	Synthetic	18/7/2017	6.46	1,330.00	0.19
ROLL	iShares Bl. Enh. Roll Yield Com. Swap UCITS ETF	Bloomberg Enhanced Roll Yield TRI	ISHARES	Synthetic	28/9/2018	5.26	1,240.00	0.28
EXXY	iShares Diversified Commodity Swap UCITS ETF (DE)	Bloomberg Commodity TRI	ISHARES	Synthetic	7/8/2007	16.41	256.09	0.46
IGLD	iShares Physical Gold EUR Hedged ETC	ICE LBMA Gold EUR Hedged Index	ISHARES	Physical	5/7/2022	1.49	24.64	0.25
GBS	Gold Bullion Securities	Gold Spot	WISDOM TREE	Physical	31/3/2004	19.76	2,630.00	0.40
PHAG	WisdomTree Physical Silver	Silver	WISDOM TREE	Physical	24/4/2007	16.70	1,150.00	0.49
PHAU	WisdomTree Physical Gold	Gold Spot	WISDOM TREE	Physical	24/4/2007	16.70	4,260.00	0.39
PHPD	WisdomTree Physical Palladium	Palladium	WISDOM TREE	Physical	24/4/2007	16.70	84.69	0.49
PHPT	WisdomTree Physical Platinum	Platinum	WISDOM TREE	Physical	24/4/2007	16.70	8,920.00	0.49
WGLD	WisdomTree Core Physical Gold	Gold Spot	WISDOM TREE	Physical	3/12/2020	3.08	625.72	0.12

[1] About 270 commodity ETFs (ETCs) are traded on the LSE. However, there are no publicly available data for the majority of these ETFs and especially for their benchmarks. As a corollary, our sample is a relatively small portion of the entire population of the UK-listed commodity ETFs.

Symbol	Name	Benchmark	Provider	Replication	Inception Date	Age[1]	Assets ($M)[1]	Expense Ratio
COTN	WisdomTree Cotton	Cotton	WISDOM TREE	Synthetic	27/9/2006	17.27	5.36	0.49
COPA	WisdomTree Coper	Copper	WISDOM TREE	Synthetic	27/9/2006	17.27	1,460.00	0.49
COFF	WisdomTree Coffee	Coffee	WISDOM TREE	Synthetic	27/9/2006	17.27	29.32	0.49
SUGA	WisdomTree Sugar	Sugar	WISDOM TREE	Synthetic	27/9/2006	17.27	10.04	0.49
BRND	WisdomTree Bloomberg Brent Crude Oil	Brent Crude Oil	WISDOM TREE	Synthetic	9/4/2015	8.73	10.67	0.25
Average						**11.36**	**1,995.86**	**0.30**
Min						**1.49**	**5.36**	**0.11**
Max						**19.76**	**14,200.00**	**0.49**

[1]As at 31/12/2023

Note: This table presents the profiles of ETFs, which include their symbol, name, benchmark, provider, replication method, inception date, age as at 31/12/2023, net assets as at 31/12/2023, and expense ratio.

Table 2 includes the descriptive statistics of ETFs' and underlying benchmarks' daily returns. Return has been calculated in raw terms by dividing the difference between the close trade price of each ETF on day t and day t-1 by the close trade price on day t-1. The return of benchmarks has been calculated in the same way with daily close prices. The descriptive statistics are presented over the entire trading history of each ETF. The average daily return of ETFs and benchmarks is 2.4 and 2.8 bps, respectively. The median return of ETFs is higher than that of benchmarks (3.3 bps vs 1.3 bps, respectively). The average risk of ETFs is equal to 1.497, being slightly lower than the average risk of benchmarks. The average extreme returns of ETFs (and benchmarks) range from -9.39% (-11.25%) to 8.68% (10.63%). At the historical cumulative level, the average return of ETFs is 16.1%. The corresponding average return of benchmarks is 17.9%.

Table 2: Descriptive Statistics of Returns

Panel A: ETFs									
Symbol	**Average %**	**Median %**	**StDev %**	**Min %**	**Max %**	**Tot.Ret. %**	**Skew**	**Kurt**	**Obs**
RMAU	0.032	0.061	0.996	-4.937	5.492	29.569	-0.197	3.518	976
XGLD	0.014	0.019	0.972	-8.350	5.865	35.558	-0.391	4.964	3,212
XGDU	0.024	0.035	0.922	-4.927	4.110	20.370	-0.370	2.847	930
XPPT	0.043	0.077	1.920	-8.217	6.535	25.433	-0.186	0.644	934
XSLR	0.065	0.029	1.866	-9.749	7.375	54.999	0.005	2.460	925
SGLD	0.014	0.020	0.973	-8.245	5.874	35.999	-0.378	5.127	3,212
SPPT	0.030	0.143	2.003	-12.305	12.650	10.706	-0.328	3.863	1,037
SSLV	-0.001	0.014	1.820	-11.560	9.629	-43.417	-0.425	5.028	3,208
IGLN	0.015	0.021	0.974	-8.481	5.853	36.816	-0.430	5.385	3,212
IGLG	0.035	0.016	0.852	-2.838	2.847	12.300	0.239	1.263	374
IPDM	0.032	0.000	2.148	-18.802	19.598	34.677	-0.009	8.158	3,212
IPLT	0.030	0.111	2.003	-11.761	12.366	10.829	-0.307	3.515	1,037
ISLN	-0.001	0.022	1.821	-11.597	9.470	-43.442	-0.432	4.838	3,212
ICOM	0.021	0.034	0.953	-4.737	4.569	31.750	-0.405	3.263	1,629
ROLL	0.029	0.053	0.965	-5.136	4.636	37.393	-0.413	3.367	1,322
EXXY	-0.003	0.000	0.990	-6.570	7.158	-26.867	-0.175	3.306	4,141
IGLD	0.032	-0.023	0.843	-2.430	3.153	11.191	0.456	1.264	375
GBS	0.014	0.017	0.979	-7.978	5.835	33.260	-0.323	4.966	3,212
PHAG	-0.002	0.032	1.816	-11.158	9.676	-44.715	-0.427	4.801	3,212
PHAU	0.014	0.017	0.973	-8.176	5.945	33.533	-0.347	5.067	3,212
PHPD	0.032	0.055	2.148	-18.004	19.129	32.491	0.048	8.236	3,212
PHPT	0.029	0.127	2.021	-11.850	15.093	9.650	-0.169	5.202	1,037
WGLD	0.024	0.032	0.884	-4.584	4.228	16.831	-0.095	2.391	775
COTN	0.020	0.000	1.803	-10.781	10.744	17.804	0.231	3.466	4,040
COPA	0.018	0.000	1.959	-10.863	12.328	-5.601	0.089	2.494	4,040
COFF	0.055	0.000	2.033	-8.470	9.011	52.498	0.213	0.945	1,239
SUGA	0.013	0.000	1.869	-11.646	8.524	-16.191	0.002	1.596	4,040
BRND	0.047	0.000	2.425	-19.005	15.299	48.600	-0.068	7.867	2,209
Average	**0.024**	**0.033**	**1.497**	**-9.398**	**8.678**	**16.144**	**-0.164**	**3.923**	**2,256**
Min	**-0.003**	**-0.023**	**0.843**	**-19.005**	**2.847**	**-44.715**	**-0.432**	**0.644**	**374**
Max	**0.065**	**0.143**	**2.425**	**-2.430**	**19.598**	**54.999**	**0.456**	**8.236**	**4,141**

Panel B: Benchmarks									
Symbol	Average %	Median %	StDev %	Min %	Max %	Tot.Ret. %	Skew	Kurt	Obs
RMAU	0.032	0.026	1.005	-5.128	5.267	29.546	-0.239	3.304	976
XGLD	0.015	0.014	0.987	-9.150	5.267	40.347	-0.385	5.640	3,212
XGDU	0.024	0.026	0.933	-5.128	3.552	19.765	-0.277	2.287	930
XPPT	0.050	0.082	2.573	-9.834	9.847	17.350	0.007	2.701	934
XSLR	0.068	0.000	1.946	-8.734	10.748	56.874	0.392	3.277	925
SGLD	0.015	0.014	0.987	-9.150	5.267	40.347	-0.385	5.640	3,212
SPPT	0.035	0.000	2.604	-13.427	10.939	0.946	-0.056	3.336	1,037
SSLV	0.002	0.000	1.927	-17.787	18.963	-41.751	-0.268	12.449	3,208
IGLN	0.015	0.014	0.987	-9.150	5.267	40.347	-0.385	5.640	3,212
IGLG	0.040	-0.002	0.857	-3.319	3.156	16.011	0.311	1.562	374
IPDM	0.033	0.000	2.129	-14.510	18.485	40.226	-0.255	6.984	3,212
IPLT	0.035	0.000	2.604	-13.427	10.939	0.946	-0.056	3.336	1,037
ISLN	0.002	0.000	1.927	-17.787	18.963	-40.850	-0.268	12.436	3,212
ICOM	0.023	0.064	0.981	-6.059	7.465	34.117	-0.325	5.448	1,629
ROLL	0.032	0.062	0.947	-5.523	3.564	40.383	-0.544	2.993	1,322
EXXY	0.004	0.000	1.204	-15.903	17.538	-13.400	0.634	53.006	4,141
IGLD	0.035	-0.006	0.857	-3.307	3.154	12.560	0.316	1.552	375
GBS	0.015	0.014	0.987	-9.150	5.267	40.347	-0.385	5.640	3,212
PHAG	0.002	0.000	1.927	-17.787	18.963	-40.850	-0.268	12.436	3,212
PHAU	0.015	0.014	0.987	-9.150	5.267	40.347	-0.385	5.640	3,212
PHPD	0.033	0.000	2.129	-14.510	18.485	40.226	-0.255	6.984	3,212
PHPT	0.035	0.000	2.604	-13.427	10.939	0.946	-0.056	3.336	1,037
WGLD	0.023	0.008	0.889	-4.410	3.208	16.232	-0.046	1.698	775
COTN	0.022	0.000	1.875	-23.885	9.064	17.596	-0.689	9.051	4,040
COPA	0.020	0.000	1.671	-10.744	12.500	-4.213	0.057	3.998	4,040
COFF	0.071	0.000	2.235	-8.626	10.028	57.809	0.317	1.119	1,239
SUGA	0.038	0.000	2.074	-11.632	13.953	-13.799	0.097	3.110	4,040
BRND	0.048	0.045	2.613	-24.404	31.547	51.921	0.320	17.492	2,209
Average	**0.028**	**0.013**	**1.623**	**-11.252**	**10.629**	**17.869**	**-0.110**	**7.218**	**2,256**
Min	**0.002**	**-0.006**	**0.857**	**-24.404**	**3.154**	**-41.751**	**-0.689**	**1.119**	**374**
Max	**0.071**	**0.082**	**2.613**	**-3.307**	**31.547**	**57.809**	**0.634**	**53.006**	**4,141**

Note: This table presents the descriptive statistics of ETFs and benchmarks' returns, which include average and median daily returns, standard deviation of returns, minimum and maximum values, and the skewness and kurtosis estimates. Total (cumulative) returns over the entire trading history of each ETF are presented too.

2.2 Research Methods

First, we evaluate the performance of commodity ETFs via the following time series regression model:

$$R_{cp,i} = \alpha_0 + \beta_1 R_{b,i} + u \qquad (1)$$

where $R_{cp,i}$ is the daily return of the commodity ETF i and $R_{b,}$ is the daily return of the underlying commodity or commodity index i. If the examined ETFs are fully aligned with the underlying assets, alphas will be statistically insignificant, while beta will be close to unity.

After running model (1) for each ETF in the sample, we compute tracking errors in four ways found in Frino and Gallagher (2001). The first method (TE_1) regards the average daily difference in returns between ETFs and benchmarks. The second method (TE_2) concerns the total (cumulative) tracking error over the entire trading history of each ETF. The third method (TE_3) regards the standard deviation in return differences between ETFs and benchmarks. The fourth method (TE_4) concerns the standard errors of the performance regression model (1)[2].

[2] According to Frino and Gallagher (2001), tracking errors obtained from the third and the fourth method will approximate each other provided that betas estimated by model (1) will be close to unity.

In the next step, we assess the impact on tracking error by the possible departure of ETFs from a full replication policy by running the following cross-sectional regression model:

$$TE = \lambda_0 + \lambda_1 NFR + \lambda_2 ReplMet + \lambda_3 Age + \lambda_4 ExpRatio + \lambda_5 Assets + u \qquad (2)$$

where TE is the tracking error estimated via methods 1 to 4, NFR (non-full replication) is the difference between model's (1) betas from unity, ReplMet refers to replication method, which is a dummy variable taking zero value when the ETF applies physical replication and 1 when the ETF pursues synthetic replication, Age is the natural logarithm of ETFs' age as at 31/12/2023, ExpRatio is the expense ratio of ETFs, and Assets regard the natural logarithm of ETFs' assets as at 31/12/2023.

In this model, we assume that the larger the gap between beta and unity, the highest the tracking error of ETFs, either positive or negative. In addition, based on findings in the literature (e.g., Fasas, 2014, and Rompotis, 2016), the physically backed ETFs are expected to have lower tracking error than synthetic ETFs. Thus, the ReplMet (replication method) coefficient is expected to be positive, as the constant of the model captures the tracking error of the physically backed ETFs and λ2 indicates the difference in tracking errors between synthetic and physical ETFs. Furthermore, as age can reflect the accumulated experience and skill of an ETF's manager, the relevant coefficient in model (2) is expected to be negative, indicating that the oldest the ETF, the lowest its tracking error. Moreover, as expenses are considered to be one of the major causes of tracking error (Frino and Gallagher, 2001, and Chu, 2011), the correlation between expense ratio and tracking error in model (2) should be positive. Finally, Chu (2011) and Drenovak et al. (2014) find that the size (assets) of a fund is negatively related the fund's tracking error indicating that big funds are more capable of tracking their benchmark than small funds. Thus, the coefficient of assets in model (2) is expected to be negative.

Along with the assessment of the impact on tracking error by the factors included in model (2), we examine if (and how) the size of the tracking error depends on the ETFs' managing company. We do so by applying the following cross-sectional regression model:

$$TE = \lambda_0 + \lambda_1 DWS + \lambda_2 Invesco + \lambda_3 iShares + \lambda_4 WisdomTree + u \qquad (3)$$

where TE is defined as above. DWS is a dummy variable with value of 1 when the ETF is provided by DWS and zero otherwise. Invesco is a dummy variable with value of 1 when the ETF is provided by Invesco and zero otherwise. iShares is a dummy variable taking value 1 when the ETF is provided by BlackRock and zero otherwise. Finally, Wisdom Tree is a dummy variable with value 1 when the ETF is provided by Wisdom Tree and zero otherwise. The constant of the model captures the tracking error of the one ETF managed by HANETF. Significant differences in tracking errors among the managing firms are to be verified by statistically significant coefficients of the dummy variables.
In the last step, we analyse further the tracking error of the examined commodity ETFs by summing for each ETF the number of days with nil tracking error, negative tracking error and positive tracking error, respectively.

3. Results

The results of model (1) on the performance of commodity ETFs are presented in Table 3. The average alpha of the sample is actually nil. In addition, with no exceptions, alphas are not statistically significant. This finding is not surprising as the examined ETFs do not seek to beat their underlying commodities and indexes.

Table 3: Descriptive Statistics of Returns

Symbol	alpha	t-stat[1]	beta	t-stat[2]	R-2	Obs	NFR
RMAU	0.005	0.283	0.851[a]	-9.129	0.737	976	0.149
XGLD	0.001	0.134	0.844[a]	-17.367	0.734	3,212	0.156
XGDU	0.004	0.264	0.844[a]	-9.258	0.729	930	0.156
XPPT	0.024	0.444	0.666[a]	-15.680	0.413	934	0.334
XSLR	0.028	0.553	0.546[a]	-17.491	0.324	925	0.454
SGLD	0.001	0.134	0.853[a]	-16.884	0.748	3,212	0.147
SPPT	0.016	0.302	0.597[a]	-19.664	0.467	1,037	0.403
SSLV	-0.002	-0.081	0.552[a]	-33.093	0.342	3,208	0.448
IGLN	0.001	0.161	0.849[a]	-16.995	0.740	3,212	0.151
IGLG	-0.001	-0.027	0.814[a]	-6.278	0.671	374	0.186
IPDM	0.008	0.304	0.735[a]	-21.731	0.531	3,212	0.265
IPLT	0.016	0.305	0.595a	-19.741	0.464	1,037	0.405
ISLN	-0.002	-0.090	0.554[a]	-33.025	0.343	3,212	0.446
ICOM	0.003	0.230	0.808[a]	-14.357	0.692	1,629	0.192
ROLL	0.003	0.208	0.851[a]	-9.648	0.697	1,322	0.149
EXXY	-0.005	-0.558	0.659[a]	-44.589	0.643	4,141	0.341
IGLD	-0.002	-0.164	0.953[a]	-3.745	0.940	375	0.047
GBS	0.001	0.066	0.852[a]	-16.496	0.739	3,212	0.148
PHAG	-0.003	-0.122	0.554[a]	-33.155	0.346	3,212	0.446
PHAU	0.001	0.072	0.850[a]	-16.988	0.743	3,212	0.150
PHPD	0.007	0.279	0.740a	-21.484	0.538	3,212	0.260
PHPT	0.015	0.286	0.600[a]	-19.362	0.465	1,037	0.400
WGLD	0.004	0.250	0.850[a]	-8.075	0.730	775	0.150
COTN	0.006	0.290	0.653[a]	-31.244	0.462	4,040	0.347
COPA	0.012	0.389	0.651[a]	-19.615	0.698	4,040	0.349
COFF	0.000	-0.007	0.769[a]	-16.737	0.716	1,239	0.231
SUGA	-0.012	-0.645	0.680[a]	-34.398	0.569	4,040	0.320
BRND	0.037	0.738	0.622[a]	-19.700	0.455	2,209	0.378
Average	**0.006**	**0.143**	**0.728**	**-19.497**	**0.596**	**2,256**	**0.272**
Min	**-0.012**	**-0.645**	**0.546**	**-44.589**	**0.324**	**374**	**0.047**
Max	**0.037**	**0.738**	**0.953**	**-3.745**	**0.940**	**4,141**	**0.454**

[1] t-stat for alphas being statistically different from zero; [2] t-stat for betas being statistically different from unity
[a] Statistically significant at 1%
NFR= Non Full Replication as evidenced by the differences between ETFs' betas and unity.
Note: This table presents the results of a single factor time series regression model in which the daily return of each ETF is regressed on the corresponding return of its benchmark.

The average beta is 0.73 indicating that the sample's commodity ETFs are quite aligned to their tracking assets. However, by focusing on the single beta estimates, we see that all beta estimates are statistically different from unity. Overall, betas indicate that the examined UK-listed commodity ETFs are not fully aligned with their underlying benchmarks. This departure from the full alignment (amounting to 0.27 on average as shown in Table 3) may be indicative of significant tracking errors.

Indeed, as we see in Table 4, the examined commodity ETFs fail to fully replicate the performance of their benchmarks. At the daily level, the average tracking error of the sample is slightly negative at -0.5 bps. Twenty four out of the twenty eight ETFs present negative tracking error. This negative tracking error indicates that the corresponding ETFs underperform their benchmarks.

Table 4: Measures of Tracking Error

Ticker	TE_1 (Average)	TE_2 (Total)	TE_3 (StDev)	TE_4 (SE)	Min	Max	Obs
RMAU	0.000	0.022	0.532	0.511	-2.682	3.189	976
XGLD	-0.001	-4.789	0.525	0.502	-3.395	3.875	3,212
XGDU	0.000	0.605	0.502	0.480	-2.312	2.237	930
XPPT	-0.008	8.083	1.335	1.073	-10.015	8.698	934
XSLR	-0.003	-1.876	1.770	1.534	-7.162	7.984	925
SGLD	-0.001	-4.348	0.509	0.488	-3.397	3.572	3,212
SPPT	-0.005	9.761	1.324	1.172	-9.983	12.144	1,037
SSLV	-0.003	-1.667	1.709	1.476	-11.839	9.869	3,208
IGLN	-0.001	-3.531	0.519	0.497	-3.394	3.659	3,212
IGLG	-0.009	-3.711	0.514	0.489	-2.361	2.236	374
IPDM	-0.001	-5.549	1.576	1.472	-11.997	14.994	3,212
IPLT	-0.005	9.884	1.332	1.072	-10.092	12.200	1,037
ISLN	-0.003	-2.591	1.708	1.476	-11.904	10.063	3,212
ICOM	-0.001	-2.367	0.562	0.529	-6.865	5.848	1,629
ROLL	-0.001	-2.990	0.549	0.531	-3.965	4.121	1,322
EXXY	-0.006	-13.467	0.720	0.592	-17.382	14.746	4,141
IGLD	-0.003	-1.369	0.210	0.206	-2.109	1.408	375
GBS	-0.002	-7.087	0.521	0.500	-3.279	3.515	3,212
PHAG	-0.004	-3.865	1.702	1.469	-12.597	10.270	3,212
PHAU	-0.002	-6.814	0.515	0.493	-3.345	3.832	3,212
PHPD	-0.001	-7.734	1.560	1.459	-12.173	14.526	3,212
PHPT	-0.006	8.704	1.133	0.933	-9.975	11.873	1,037
WGLD	0.001	0.599	0.478	0.459	-2.332	2.234	775
COTN	-0.002	0.208	1.473	1.322	-7.900	9.431	4,040
COPA	-0.002	-1.388	0.914	0.790	-10.733	11.023	4,040
COFF	-0.017	-5.312	1.200	1.084	-6.826	11.316	1,239
SUGA	-0.025	-2.392	1.395	1.227	-12.071	10.485	4,040
BRND	0.000	-3.321	1.219	1.057	-11.753	10.651	2,209
Average	**-0.005**	**-3.199**	**0.991**	**0.883**	**-8.451**	**8.459**	**2,256**
Min	**-0.025**	**-13.467**	**0.210**	**0.206**	**-17.382**	**1.408**	**374**
Max	**0.001**	**8.704**	**1.708**	**1.476**	**-2.109**	**14.746**	**4,141**

Note: This table presents the tracking error of ETFs. Tracking error is calculated in four alternative ways, that is, i) average daily return difference between ETFs and benchmarks, ii) total (cumulative) tracking errors over the entire trading history of each ETF, iii) standard deviation in daily return differences between ETFs and benchmarks, and iv) sum of standard errors (SE) deriving from the single factor regression model where the daily return of each ETF is regressed on the corresponding return of its benchmark, Extreme daily tracking errors are reported too.

The underperformance of ETFs is more evident when cumulative tracking errors are taken into consideration. The respective average term is 3.2% (or 320 bps). Maximum underperformance is -13.5%, while maximum outperformance is 8.7%. These extreme tracking errors are shown by the iShares Diversified Commodity Swap UCITS ETF (DE) and the WisdomTree Physical Platinum, i.e., two of the ETFs that significantly depart from the full replication, as inferred by their betas which significantly decline from unity.

The next two methods used to calculate tracking error also indicate that the return gap between commodity ETFs and their benchmarks is significant. The average TE_3 of the sample is equal to 99 ps. The average TE4 equals 88 bps. To some extent, the difference of 11 bps between the average TE3 and TE_4 tracking error figures must be the result of beta estimates in Table (3) being lower than unity by an average of 27 bps. Other factors can explain tracking error too.

In fact, as reported in Table 5, the coefficients of NFR are positive and statistically significant for TE2, TE3 and TE4, verifying our expectations about a positive correlation between tracking error and the departure from the full replication strategy. The results on the dummy concerning the replication method are also in agreement with our assumption about physical ETFs being more efficient in replicating their benchmarks compared to their synthetic peers. In particular, the relevant coefficients for TE3 and TE4 are significantly positive indicating that the synthetic ETFs have higher tracking error than the physically backed ETFs.[3]

Table 5: Tracking Error Per Factors Regression Results

	Dep. Var.: TE1		Dep. Var.: TE2		Dep. Var.: TE3		Dep. Var.: TE4	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	0.01	1.53	-0.51	-0.04	1.35[a]	3.18	1.35[a]	3.25
NFR	0.00	0.22	19.67[c]	1.89	2.80[a]	6.98	2.13[a]	5.42
Repl. Method	0.00	-0.53	-2.37	-1.07	0.22[b]	2.14	0.19[c]	1.94
Age	0.00	0.22	-1.87	-1.06	0.16[b]	2.20	0.16[b]	2.33
Expense Ratio	0.01[b]	2.07	-3.38	-0.32	0.01	0.02	-0.06	-0.16
Assets	0.00	-1.44	-0.04	-0.06	-0.07[a]	-3.51	-0.07[a]	-3.40
R-2	0.34		0.26		0.85		0.81	
Obs	28		28		28		28	

[a] Statistically significant at 1%; [b] Statistically significant at 5%; [c] Statistically significant at 10%

Note 1: This table presents the results of a cross-sectional regression model in which the tracking errors of ETFs is regressed on their non-full replication policy (NFR) as evidenced by the differences between their betas (in Table 3) and unity, replication method, that is, a dummy variable taking zero value when the ETF applies physical replication and one when the ETF pursues synthetic replication, age as at 31/12/2023, expense ratio, and assets as at 31/12/2023.

Note 2: The absolute value of TE_1 and TE_2 is used in this model.

Going further, the coefficients of age in Table 5 are significantly positive for TE3 and TE4 and insignificant for TE1 and TE2. The significantly positive estimates for age contradict our assumption about the positive impact on the tracking ability of an ETF exerted by the accumulated experience of the ETF's manager as the latter may be reflected by the age of ETFs. Moreover, our assumption about the positive correlation between tracking error and expense ratios is verified only for TE1. Finally, our expectation about the negative relationship between tracking error and the magnitude of ETFs' assets is verified. In particular, the estimates of the assets factor are significantly negative for TE3 and TE4.

Based on the regression results, we can conclude that the five determinative factors included in model (2) are quite capable of explaining the tracking error of the UK-listed commodity ETFs. This ability is verified by the relatively high R-squared values, especially for TE3 and TE4. However, this is not the case when assessing the impact on tracking error by the individual providers of commodity ETFs included in model (3). As shown in Table (6), all the relevant estimates are statistically insignificant indicating that there are no statistically and economically differences in the tracking efficiency among the five managing companies considered in our analysis.

[3] The average TE3 (TE4) of physical ETFs amounts to 0.999% (0.888%). The corresponding figures for synthetic ETFs are 1.004% and 0.892%.

Table 6: Tracking Error Per Provider Regression Results

	Dep. Var.: TE1		Dep. Var.: TE2		Dep. Var.: TE3		Dep. Var.: TE4	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	0.00	0.01	0.02	0.00	0.53	1.03	0.51	1.17
DWS	0.00	0.47	0.48	0.08	0.50	0.86	0.39	0.79
Invesco	0.00	0.46	1.23	0.19	0.65	1.08	0.53	1.06
iShares	0.00	0.58	-2.88	-0.49	0.32	0.59	0.25	0.54
Wisdom Tree	0.01	0.93	-2.60	-0.45	0.57	1.05	0.47	1.03
R-2	0.07		0.09		0.09		0.09	
Obs	28		28		28		28	

Note 1: This table presents the results of a cross-sectional regression model in which the constant expresses the ETFs managed by HANETF and four dummy variables for ETFs managed by DWS, Invesco, iShares (BlackRock), and Wisdom Tree, respectively.
Note 2: The absolute value of TE_1 and TE_2 is used in this model.

The decomposition of daily tracking errors is presented in Table 7. More specifically, the table shows that, on average, ETFs achieve zero tracking errors just in 0.35% of total trading days. Positive tracking errors are computed in about 47% of trading days. The average positive daily tracking error (outperformance) amounts to 84 bps. On the other hand, negative tracking errors are realised in about 52% of trading days. The average negative daily tracking error is equal to -84 bps. In sum, the ETFs under study underperform their benchmarks slightly more frequently than they outperform them.

Table 7: Analysis of Daily Tracking Error

Ticker	Nil TE	% Nil TE	Posit. TE	% Pos. TE	Av. Posiv. TE	Neg. TE	% Neg. TE	Av. Neg. TE	Obs
RMAU	0	0.00%	486	49.80%	0.396	490	50.20%	-0.392	976
XGLD	1	0.03%	1,593	49.60%	0.375	1,618	50.37%	-0.371	3,212
XGDU	0	0.00%	463	49.78%	0.385	467	50.22%	-0.381	930
XPPT	0	0.00%	470	50.32%	1.570	464	49.68%	-1.610	934
XSLR	0	0.00%	470	50.81%	1.359	455	49.19%	-1.409	925
SGLD	1	0.03%	1,602	49.88%	0.367	1,609	50.09%	-0.368	3,212
SPPT	0	0.00%	524	50.53%	1.554	513	49.47%	-1.597	1,037
SSLV	0	0.00%	1,590	49.56%	1.262	1,618	50.44%	-1.246	3,208
IGLN	1	0.03%	1,591	49.53%	0.375	1,620	50.44%	-0.370	3,212
IGLG	0	0.00%	181	48.40%	0.380	193	51.60%	-0.373	374
IPDM	8	0.25%	1,611	50.16%	1.127	1,593	49.60%	-1.141	3,212
IPLT	1	0.10%	523	50.43%	1.563	513	49.47%	-1.603	1,037
ISLN	1	0.03%	1,592	49.56%	1.260	1,619	50.40%	-1.246	3,212
ICOM	4	0.25%	818	50.21%	0.386	807	49.54%	-0.393	1,629
ROLL	1	0.08%	667	50.45%	0.381	654	49.47%	-0.391	1,322
EXXY	37	0.89%	610	14.73%	0.419	3,494	84.38%	-0.080	4,141
IGLD	0	0.00%	79	21.07%	0.078	296	78.93%	-0.025	375
GBS	1	0.03%	1,583	49.28%	0.377	1,628	50.68%	-0.370	3,212
PHAG	4	0.12%	1,579	49.16%	1.263	1,629	50.72%	-1.233	3,212
PHAU	2	0.06%	1,593	49.60%	0.371	1,617	50.34%	-0.369	3,212
PHPD	5	0.16%	1,611	50.16%	1.113	1,596	49.69%	-1.126	3,212
PHPT	0	0.00%	523	50.43%	1.556	514	49.57%	-1.594	1,037
WGLD	0	0.00%	378	48.77%	0.374	397	51.23%	-0.356	775
COTN	14	0.35%	2,003	49.58%	0.974	2,023	50.07%	-0.967	4,040
COPA	262	6.49%	1,900	47.03%	1.611	1,878	46.49%	-1.634	4,040
COFF	2	0.16%	616	49.72%	0.830	621	50.12%	-0.856	1,239
SUGA	10	0.25%	2,036	50.40%	0.885	1,994	49.36%	-0.953	4,040
BRND	8	0.36%	1,095	49.57%	1.040	1,106	50.07%	-1.010	2,209
Average	**13**	**0.35%**	**1,064**	**47.45%**	**0.844**	**1,180**	**52.21%**	**-0.838**	**2,256**
Min	**0**	**0.00%**	**79**	**14.73%**	**0.078**	**193**	**46.49%**	**-1.634**	**374**
Max	**262**	**6.49%**	**2,036**	**50.81%**	**1.611**	**3,494**	**84.38%**	**-0.025**	**4,141**

Note: This table presents an analysis of ETFs' daily tracking error. This analysis considers the number of days where ETFs present zero tracking error, the number of days where tracking error is positive, and the number of days where tracking error is negative.

A last comment that should be made with respect to the tracking efficiency of ETFs, is that, despite the presence of ETFs for about three decades now (given that the US-listed SPDRs tracking the S&P 500 Index was the first ETF to enter the stock markets worldwide in 1993), tracking inefficiencies are still there, as they used to be during the first years of ETFs' existence. These inefficiencies must relate to inherent frictions attached to the passively managed ETFs which try to replicate the return of benchmarks which are not affected by expenses, age, assets and other factors that affect the replication efforts of ETFs. These frictions have been accentuated by several studies in literature and are confirmed by the current study too.

4. Conclusion

The performance and tracking efficiency of twenty eight commodity ETFs that are traded on the London Stock Exchange are examined in this study. The analysis shows that the average daily and cumulative return of these ETFs has been positive during their entire trading history. However, the return of ETFs has been inferior to the return of their underlying commodities and indexes by 320 bps, indicating a significant tracking inefficiency. Tracking inefficiency is verified by all the methods used to compute the tracking error of the examined commodity ETFs.

One key factor that can provoke tracking inefficiency relates to the inability of ETFs to be fully aligned with their underlying assets. Non-full alignment might also be a choice made by the examined commodity ETFs. In any case, the departure from the full replication is inferred by the fact that the beta estimates obtained from the performance regression model differ statistically from unity in eight out of nine cases. By relevant regression analysis, it is verified that the non-full alignment to underlying benchmarks is positively related to the tracking error of ETFs, which, by the way, is negative on about 52% of days over the entire trading history of commodity ETFs in the UK. Other factors that can induce tracking error include the replication method applied by ETFs, their age, assets, and, to a less degree, their expense ratio.

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RESILIENCE OF ORGANISATION CAPITAL ON FIRMS' PERFORMANCE AMID CRISIS

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Abstract

Drawing on the concept of organisation capital as an intangible asset perspective, we examine the relationship between organisation capital and Australia firms' performance and its moderating effects during the last two crisis periods, i.e., Global Financial Crisis (GFC) and COVID-19. We find that higher investment in organisation capital will result in lower drops in firm's performance. Long-term investment in organisation capital would help to improve firm's performance and mitigate the Changes in ROA in crisis. A resilience picture through organisation capital is pictured.

Keywords: organisation capital, crisis resilience, drops in firm performance, firm-specific crisis severity

1. Introduction

The recent COVID-19 crisis has instigated economic disruptions that affected nearly every aspect of life more than that during the 2008/09 Global Financial Crisis (GFC), posing a direct threat to business in different societies by both public and private organisations. Operating in a more volatile and dynamic environment more than ever, survival and growth become a central goal for most businesses. It raises questions such as: What practices should business organisations possess to survive this adverse environmental condition? Can we plan-ahead to preserve performance and weather the next crisis? The last two crises (GFC, COVID-19) and their severe economic and social consequences provide a unique setting to examine the organisation capital and their impact on businesses' resilience, sustainability, and competitiveness through difficult times.

Much research has been conducted to explain what we know about the crisis-organisation interaction and how to develop organisational resilience to respond to adversity but also to mitigate it before it arises (Williams, Gruber, Sutcliffe, Shepherd, & Zhao, 2017). The term resilience was first used by Holling's (1973) work on ecological systems and then used in different contexts (such as physical systems, socioecological systems, psychology, and disaster management) to outline the ability of a system to return to a steady state after disruption (Delilah Roque, Pijawka, & Wutich, 2020). Aside from the environmental and physical dimensions that resiliency theory focuses on, studies of organisational resilience have also been developed. Organisational resilience is defined as the ability to absorb strain and preserve, to survive, adapt and grow (or improve) functioning in the presence of turbulent changes that may threaten organisation survival (Cumming et al., 2005; Fiksel, 2006; Lengnick-Hall, Beck, & Lengnick-Hall, 2011; Ponis & Koronis, 2012; Sutcliffe & Vogus, 2003), which has been a newer tradition in management theory that incorporates insights from both coping and contingency theories (Koronis & Ponis, 2018). Myer and Moore (2006) (p. 143) indicate that there is a "reciprocal effect of crises on individuals and organisations. If these relationships are supportive, the impact of the crisis can be reduced; if they are obstructive, the impact has the potential to be severe". Therefore, organisational resilience is the ability to absorb crisis, trauma or radical change and maintain or exceed the previous performance levels (Horne III, 1997).

The 1990s organisational resilience studies focused on the individual resilience of employees (Doe, 1994; Egeland, Carlson, & Sroufe, 1993), and the collective actions of employees that constitute the organisational response to change (Home III & Orr, 1997). Concepts of resilience at the organisational level expands in the 2000s (Caralli, 2006; Gunderson, 2000; Myer & Moore, 2006; Riolli & Savicki, 2003; Sundström & Hollnagel, 2017). Facing with the environment of uncertainty and unpredictability, contributions to corporate resilience and growth include increased buffering capacity (Gunderson, 2000); strong relational assets such as financial reserves (Gittell, Cameron, Lim, & Rivas, 2006); increased preparedness (Koronis & Ponis, 2018), good governance and balanced growth (Carmeli & Markman, 2011), and investment in intangible capital (Haskel & Westlake, 2017).

Organisation capital as one of the prominent components of the intangible assets of the economy has documented the strong complementarity between organisation and knowledge capital in improving firm (and national) innovation, growth, and competitiveness (Bresnahan, Brynjolfsson, & Hitt, 2002; Brynjolfsson, Hitt, & Yang, 2002). Lev, Radhakrishnan, and Zhang (2009) also show that organisation capital is a persistent creator of value and growth for business enterprises. They also suggest that the contribution made by organisation capital is generally manifested in sustained growth in sales, earnings, and market value. Uddin, Hasan and Abadi (2022) also find that firms' intangibles such as internally generated organisation capital could provide resilience to pandemic shocks from infectious diseases. However, the impact of organisation capital on performance and its resilience benefit during crisis periods still remain under-developed. Considering this gap in the literature, in this study we investigate whether organisation capital can act as a resilience driver to enhance the survival and recovery of organisations from the emerged crisis such as COVID-19 with the use of an Australian sample. Our contributions can be summarised as follows. First, we contribute to the literature gap by providing further evidence on the organisational resilience benefits provided by organisation capital. Second, to the best of our knowledge, there has been no study focusing on the benefits of organisation capital to Australian firms during a crisis environment. Australia provides an intriguing case study in relation to the global economic crisis. It has been claimed to have withstood the global financial crisis remarkably well, given the source of numerous laudatory statements by government officials (Hill, 2012). For example, in 2008, the Governor of the Reserve Bank of Australia commented, that "there would be very few countries, if any, which would not envy Australia's fiscal position." This statement is supported by the following Australian economic growth after the global financial crisis. In the March quarter of 2009, the Australian economy grew by 0.4 per cent. In contrast, all the G7 economies contracted in the March quarter and as a group by 2.1 per cent. Out of 33 advanced economies, only two managed to grow in the March quarter (Gruen, 2009). In addition, Australia has a diverse economy with significant sectors like mining, agriculture, manufacturing, services, and finance. It is an entrepreneurial nation, with small and medium businesses playing a significant role in Australian growth and job creation (Bloch & Bhattacharya, 2016). Therefore, studying its experiences can provide valuable lessons for policymakers and researchers globally in managing and mitigating the impact of economic crises.

This paper is designed as follows. Section 2 discusses the data sample and methodology. Section 3 presents our key empirical results. Section 4 concludes.

2. Data, variable description, and method

2.1 Data and sample

Our sample consists of 18,995 firm-level yearly observations listed on Australian Stock Exchange over the period from 2000 to 2023, covering 1,389 firms. Data were retrieved from Compustat Global via Wharton Research Data Services (WRDS) platform and LSEG Refinitiv Workspace. All financial firms are excluded. We winsorise all continuous variables at the top and bottom 1%.

2.2 Measurement of key variables

Firm performance

Changes in ROA (or Δ_{ROA}) and revenue growth (or REVG) have been used as dependent variable following the study of post-shock studies such as the 2008/09 global financial crisis (Buyl, Boone, & Wade, 2019). We assess Changes in ROA based on yearly ROA and is therefore operationalised as a company's performance (ROA) in the current financial year (i.e. time t) minus its performance in the previous financial year (i.e. time t-1). Revenue growth is computed as the percentage change in sales revenue from the previous year to the current year (i.e. from time t-1 to time t). As ROA is considered an accounting measure (or an ex-post approach to capture firm performance) which may fail to capture the future prospects of firms, we also include changes in Tobin's q (or $\Delta_{Tobin's\,q}$) from time t-1 to time t as an alternative dependent variable to take into account investors' future expectations and thus being considered as an ex-ante approach to reflect firm performance. Tobin's q is computed based on the following equation:

$$Tobin's\ q = \frac{Total\ Assets - Book\ Value\ of\ Equity + Market\ Value\ of\ Equity}{Total\ Assets} \quad (1)$$

Organisation capital

Lev and Radhakrishnan (2005); (Lev et al., 2009) use selling, general, and administrative (SG&A) expenditures as a direct measure of organisation capital (or OC). The empirical validation of organisation capital performed by Eisfeldt and Papanikolaou (2013) is supported by their analysis that Tobin's Q, executive compensation, and labour expense per employee are all monotonically increasing in organisation capital, consistent with higher organisation capital firms depending on more skilled employees and generating more output relative to their recorded assets.

So, a firm's level of organisation capital in each year is constructed as the accumulation of the depreciated value of its organisation capital in the previous year and the contemporary deflated values of SG&A expenses.

It is computed following Lev and Radhakrishnan (2009) and Eisfeldt and Papanikolaou (2013):

$$OC_{i,t} = OC_{i,t-1}\,(1 - \delta_0) + \frac{SGA_{i,t}}{cpi_t} \quad (2)$$

Where:

- $OC_{i,t}$ (and δ_0) denote the firm-specific stock of organisation capital at time t (and depreciation rate of OC).

- SGA is SG&A (selling, general, and administrative expenses).
- cpi_t is the consumer price index at time t.

The initial stock of organisation capital is estimated as the initial SG&A expense divided by the sum of the growth rate and the depreciation rate:

$$OC_{i,t0} = \frac{SGA_{i,t0}}{g+\delta_0} \quad (3)$$

Where:
- t_0 is initial year for the firm in the sample.

A 20% depreciation rate (δ_0), a growth rate (g) equals to 10% are chosen following Eisfeldt and Papanikolaou (2013)'s and Allen's (2022) studies. Zero or missing values of SG&A have been removed from the sample. Organisation capital is further scaled by total assets to make it comparable across firms.

Firm-specific crisis severity

Following Osiyevskyy, Shirokova, and Ritala (2020), the firm-specific crisis severity is estimated as the changes in two-year revenue between the crisis years (2020, 2021) and the pre-crisis years (2019, 2018) as below. The same method is applied to the 2008/09 global financial crisis.

$$Firm - specific\ crisis\ severity = 1 - \frac{Revenue_{2020}+Revenue_{2021}}{Revenue_{2019}+Revenue_{2018}} \quad (4)$$

The positive values on this variable suggest that during the crisis years, the firm suffered a drop in revenue (i.e. $\frac{Revenue_{2020}+Revenue_{2021}}{Revenue_{2019}+Revenue_{2018}} < 1$). The negative values on this variable suggest that the firm was growing despite the overall economic downturn (i.e. (⟦. $\frac{Revenue_{2020}+Revenue_{2021}}{Revenue_{2019}+Revenue_{2018}} > 1$). If there is no change in revenue, the crisis severity variable equals zero (i.e. (⟦$\frac{Revenue_{2020}+Revenue_{2021}}{Revenue_{2019}+Revenue_{2018}} = 1$).

To account for the possible factors that might affect the independent variables and the outcome variables, a set of relevant control variables are added. Table 1 presents the summary description of variable definitions.

Table 1: Variable Description

Variable	Definition
Dependent Variable	
Changes in ROA, Δ_{ROA}	Return on Asset (ROA) changes between time *t* and time *t-1*
Changes in Tobin's q, $\Delta_{Tobin's\,q}$	Tobin's q changes between time *t* and time *t-1*; Tobin's q is computed as (Total assets – book value of equity + market value of equity) / total assets
Revenue Growth, REVG	Revenue at time *t* relative to time *t-1*
Independent Variables	
Organisation Capital	It is measured as the stock of organisation capital scaled by total assets
Firm-specific Crisis Severity	Changes in two-year revenue between the crisis years (2020, 2021) and the pre-crisis years (2019, 2018)
GFC Crisis	A dummy variable that equals one if the year is 2008 or 2009, otherwise zero
Covid Crisis	A dummy variable that equals one if the year is 2020 or 2021, otherwise zero
GFC + Covid Crisis	A dummy variable that equals one if the year is 2008, 2009, 2020 or 2021, otherwise zero
Control Variables	
Firm Size	Natural logarithm of 1 plus the book value of assets.
Firm Age	Age is the age of the firm, which is calculated as the natural logarithm of 1 plus the number of years to 2023 that the company was first incorporated. Older firms might be more likely to acquire resources that help them manage negative events (e.g., human capital) (DesJardine et al., 2019)
Research & Development	Research and development expenditures to total assets
Capital Expenditure	Capital expenditures to book value of total assets
Leverage	Total long-term debt relative to total assets
Independent Board	Percentage of independent board members as reported by the company.
Chairman Duality	Does the CEO simultaneously chair the board or has the chairman of the board been the CEO of the company?
Average Board Tenure	Average number of years each board member has been on the board.

2.3 Modelling methods

Multinomial logistic regression analysis was performed to examine whether firm-specific characteristics, organisation capital and Changes in ROA can help distinguish the normal years and crisis years between 2000 and 2023. The equation can be formalised as below:

$$P(Y = j) = \frac{e^{W_j}}{1+\sum_{j=1}^{4} e^{W_j}} \tag{5}$$

Where:

- $W_j = \beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 \ldots + \beta_{jn}X_n$
- P(Y=j) represents the crisis years j (j=1 if is 2008, j=2 if it is 2009, j=3 if it is 2020, j=4 if it is 2021) is chosen against the normal or non-crisis years. The ranking of the crisis years does not imply an ordinal relationship or infer any economic ranking. Each crisis year is treated as a separate category.

A longitudinal panel data research design has been adopted to control endogeneity and unobserved heterogeneity. The Hausman test failed to reject the null hypothesis, indicating that the random-effect estimator was consistent and therefore appropriate. To account for heteroscedasticity and intragroup correlations, we clustered standard errors within the panel.

To test the impact of organisation capital on firm performance and whether organisation capital provides resilience benefits during the crisis periods, we construct the following equations as below:

$$\Delta_{ROA_{it}}/\Delta_{Tobin's\ q_{it}} = \alpha + \beta \times Independent\ variables_{it} + \gamma \times Control\ variables_{it} + \theta \times Corporate\ governance\ variables_{it} + \delta \times Interaction\ terms_{it} + \mu_j + \varepsilon_{it} \tag{6}$$

$$REVG_{it} = \alpha + \beta \times Independent\ variables_{it} + \gamma \times Control\ variables_{it} + \theta \times Corporate\ governance\ variables_{it} + \delta \times Interaction\ terms_{it} + \mu_j + \varepsilon_{it} \tag{7}$$

The dependent variables in Eq. (6) are Change in ROA and Change in Tobin's q, whereas the dependent variable in Eq. (7) is revenue growth. In Eq.(6), we include the following independent variables for our analyses: organisation capital, Global Financial Crisis (hereafter GFC) which is a dummy variable equals 1 if the year is 2008 or 2009, Covid dummy which is a dummy variable that equals 1 if the year is 2020 or 2021, and lastly Crisis dummy which is dummy variable that equals one if the year is 2008, 2009, 2020 or 2021 (i.e. GFC + Covid). In Eq. (7), we use firm-specific crisis severity and Crisis dummy as independent variables. We also include the interaction terms between organisation capital and different dummy variables (i.e. GFC, Covid, Crisis) in Eq. (6) and interaction term between organisation capital and firm-specific crisis severity in Eq.(7). We also include the following control variables in our analyses: firm size, firm age, R&D expenditures scaled by total assets, capital expenditure scaled by total assets, firm leverage and corporate governance variables such as independent board members, chairman duality and average auditor tenure. i is the firm index, t is the year index and μ_j is the industry fixed effect. Variable definitions are listed in Table 1. In order to address heteroskedasticity and autocorrelation and potential endogeneity, Eqs. (6) and (7) are estimated based on the Cross-sectional Time-series Generalised Least Squares (GLS) method as our data structure is panel data.

3. Empirical results and discussion

3.1 Descriptive statistics

Descriptive statistics are summarised in Table 2. The mean value of the changes in ROA, changes in Tobin's q and revenue growth are 0.707, 0.273 and 1.482 respectively. The mean value of organisation capital as a proportion of total assets is close to 26.4%. Descriptive statistics of the long-term leverage indicate that Australia has relatively lower long-term leverage ratios. The average research and development expense to total assets is 15.8% across all industries.

Table 2: Descriptive Statistics

	Observation	Mean	S.D.	P25	Median	P75
Changes in ROA, Δ_{ROA}	17,183	0.707	6.174	-0.689	-0.138	0.538
Changes in Tobin's q, $\Delta_{Tobin's\,q}$	15,173	0.273	1.139	-0.277	-0.007	0.368
Revenue Growth, REVG	13,164	1.482	7.283	-0.239	0.067	0.428
Firm-specific crisis severity	11,782	-2.561	12.55	-0.726	-0.110	0.371
Organisation Capital	18,781	0.264	0.749	0.008	0.033	0.159
Research & Development	4,176	0.158	0.260	0.011	0.054	0.190
Firm Size	18,995	3.239	2.059	1.801	2.828	4.334
Firm Age	18,995	2.251	0.937	1.609	2.398	2.944
Capital Expenditure	17,000	0.099	0.141	0.010	0.039	0.132
Leverage	18,780	0.069	0.143	0	0	0.068
Independent Board	2,612	62.69	21.16	50	66.67	80
Chairman Duality	2,686	0.106	0.307	0	0	0
Average Board Tenure	2,653	6.044	3.035	4.031	5.55	7.438

Note: This table reports the cross-sectional distribution (number of observations, mean, median, standard deviation, and 25th, 75th percentiles) of Australian listed firms from 2000 to 2023. Financial companies are excluded.

3.2 Multinomial logistic regression analysis

Table 3 presents the multinomial logistic regression analysis results which show the impact of variables during GFC and COVID-19 crisis periods, with the non-crisis period serving as the base or reference category. The dependent variable is the year of crisis, identified as the year of 2008, 2009, 2020 and 2021. The interpretation of the multinomial logistic regression is that for a unit change in the predictor variable, a positive coefficient implies an increase in the log-odds of being in a crisis year relative to normal periods. As presented in Table 3, we find that changes in Tobin's Q, organisation capital and firm size are statistically significant during crisis periods. Both organisation capital and firm size increased during GFC relative to normal periods but decreased during COVID-19 period. Firms' changes in Tobin's Q are found to be lower during GFC relative to normal periods but higher during COVID-19 period. This could be due to the reduction in interest rate by the Reserve Bank of Australia during the early pandemic period (Vallence & Wallis, 2021) or other factors such as digital transformation which have helped Australian firms to survive. The opposite signs of coefficients for GFC and COVID-19 periods underscore the nature of the crises. Despite the insignificance of other variables, the significant coefficients of organisation capital in different crisis periods suggest that it could act as a differentiating feature.

Table 3: Multinomial Logistic Regression Results

This table reports the multinomial logistic regression results based on Eq.(5). The dependent variable is the year of crisis, identified as the years of 2008, 2009, 2020, and 2021. The reference category is non-crisis periods, which is stated as normal in the table. A positive beta coefficient means an increased probability in the crisis period relative to the non-crisis period. A negative beta coefficient means a decreased probability in the crisis period relative to the non-crisis period.

	2008/Normal	2009/Normal	2020/Normal	2021/Normal
Changes in ROA, Δ_{ROA}	0.0343	0.0182	0.0038	-0.0138
	(0.409)	(0.349)	(0.134)	(-0.394)
Changes in Tobin's, $\Delta_{Tobin's\,q}$	-4.7558***	-1.8084*	0.6610***	0.7527***
	(-2.905)	(-1.652)	(2.925)	(3.509)
Revenue Growth	0.0073	-0.0252	-0.0290	-0.0321
	(0.058)	(-0.213)	(-0.408)	(-0.481)
Firm-specific Crisis Severity	0.0823	-0.0307*	-0.0101	-0.0217
	(0.162)	(-1.747)	(-0.495)	(-1.380)
Organisation Capital	7.1047***	4.6496***	-15.5397***	-23.7825***
	(4.076)	(2.961)	(-2.673)	(-3.095)
Firm Size	0.8819***	0.5025**	-0.1302	-0.0651
	(2.906)	(2.270)	(-1.395)	(-0.666)
Firm Age	-0.1559	0.0198	0.0276	0.1743
	(-0.290)	(0.044)	(0.095)	(0.606)
Research & Development	-4.0446	-2.8960	-0.3756	-0.5617
	(-0.487)	(-0.470)	(-0.287)	(-0.432)
Capital Expenditure	-2.6650	3.9311	0.7372	-3.3313
	(-0.301)	(0.896)	(0.318)	(-0.946)
Leverage	0.4801	-1.8043	1.5137*	0.9506
	(0.200)	(-0.885)	(1.744)	(1.003)
Independent Board	-0.0172	-0.0055	0.0191**	0.0127
	(-1.086)	(-0.381)	(2.149)	(1.498)
Chairman Duality	0.7323	0.0656	-0.0544	0.0892
	(0.818)	(0.079)	(-0.106)	(0.183)
Average Board Tenure	0.0560	-0.0118	-0.0813	-0.1001*
	(0.443)	(-0.112)	(-1.496)	(-1.857)
Constant	-10.1428***	-6.8565***	-2.1395*	-2.0004*
	(-3.411)	(-3.260)	(-1.901)	(-1.820)
Observations	710	710	710	710

Notes:
Z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Likelihood ratio chi-square = 129.83 with a p-value < 0.0001
Pseudo R^2 = 0.1152

3.3 GLS analysis results

Table 4 presents the relationship between organisational capital and firm performance, and the interaction effects between organisation capital and different crisis dummy variables on firm performance based on Eq.(6). Panel A of Table 4 considers changes in ROA as a proxy for firm performance. Models (1) to (10) report a positive relationship between organisational capital and changes in ROA. This implies that higher investment in organisational capital results in further increases in the current ROA compared to the previous year's ROA.

Out of the three crisis dummy variables, we find that Covid dummy variable has a significant and negative impact on firms' changes in ROA, with and without the inclusion of control variables in the models (the negative coefficient of Crisis dummy variable is likely caused by the significance of Covid dummy, rather than GFC dummy which becomes insignificant in later models). This result appears intuitive, as firms experienced losses during the recent pandemic.

Our most important finding is highlighted by the significance of the interaction terms between organisation capital and GFC/Covid/Crisis dummies. In models (8) to (10), we find significant and negative coefficients for interaction term between organisation capital and each dummy variable. This result implies that organisation capital potentially exacerbate the decline in ROA during crisis periods. However, this could be due to the absence of strong governance mechanisms and firms' organisation capital may not be effectively utilised. As shown in models (12) and (13), after including the corporate governance variables, we observe significant and positive coefficients for the interaction terms between organisation capital and Covid/Crisis dummies, which indicates that higher organisation capital can either mitigate the decline in ROA compared to previous year, or potentially reverse the negative impact and lead to improved firm performance during crisis time. We plot the interaction effects on changes in ROA from model (13) with separate regression lines for further visualisation of the implication (Please refer to Figure 1). As shown in Figure 1, during crisis period, organisation capital can provide firm resilience by improving their ROA. Drawing on the results presented in models (8) to (10), we postulate that organisation capital can offer firm resilience or buffering effect during crisis periods if companies have effective governance structure in place.

Table 4: GLS Model Estimates of Organisation Capital, Crisis Period, and Other Firm-Specific Features on firm performance

This table presents the relationship between organisation capital and firm performance from 2000 to 2023 based on Eqs. (6) and (7). In panel A, we use changes in ROA to capture firm performance. In Panel B, Tobin's q is used as an alternative proxy to capture firm performance. We also include the interaction terms between organisation capital and different crisis dummy variables (i.e. GFC if the year is 2008, 2009; Covid if the year is 2020, 2021 and lastly Crisis if the year is 2008, 2009, 2020, 2021).

Panel A. GLS Estimates of Organisation Capital, Crisis Periods and Changes in ROA

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Organisation Capital	0.4640***	0.4621***	0.4574***	0.4620***	0.4872***	0.5079***	0.5140***	0.6027***	0.5552***	0.4257***	1.1687	-0.2249	0.1809
	(13.356)	(13.209)	(13.117)	(13.288)	(7.412)	(7.711)	(7.843)	(8.834)	(7.674)	(6.803)	(1.319)	(-0.647)	(0.234)
GFC Dummy		0.1196***			-0.0587			0.0637			-0.1409		
		(2.594)			(-0.994)			(0.988)			(-0.561)		
Covid Dummy			-0.2297***			-0.1466***			-0.1103**			-0.2502***	
			(-7.331)			(-3.348)			(-2.276)			(-3.030)	
Crisis Dummy				-0.0861***			-0.1296***			-0.0403			-0.3246***
				(-3.309)			(-3.482)			(-1.152)			(-3.906)
Organisation Capital × GFC Dummy								-0.5675***			0.1812		
								(-3.621)			(0.095)		
Organisation Capital × Covid Dummy									-0.4244***			11.7206***	
									(-2.723)			(28.243)	
Organisation Capital × Crisis Year Dummy										-0.4329***			6.1647***
										(-4.159)			(4.872)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Control Variables													
Firm Size					-0.0129	-0.0145	-0.0133	-0.0161	-0.0150	-0.0333***	-0.0025	-0.0028	0.0026
					(-1.258)	(-1.379)	(-1.276)	(-1.575)	(-1.399)	(-4.407)	(-0.064)	(-0.083)	(0.078)
Firm Age					0.0537**	0.0647**	0.0663**	0.0608**	0.0589**	0.0256	-0.0394	-0.0011	-0.0104
					(2.118)	(2.542)	(2.576)	(2.427)	(2.284)	(1.462)	(-0.373)	(-0.012)	(-0.110)
Research & Development					1.1859***	1.2420***	1.2386***	1.2049***	1.2942***	0.6209***	1.5614***	1.5135***	1.7820***
					(11.211)	(11.725)	(11.680)	(11.393)	(11.961)	(7.696)	(4.453)	(4.760)	(5.515)
Capital Expenditure					3.1383***	3.3072***	3.3311***	3.0135***	3.1973***	2.2481***	2.9866	2.3952	1.9286
					(6.968)	(7.382)	(7.453)	(6.739)	(7.019)	(6.195)	(1.542)	(1.343)	(1.076)
Leverage					-0.0999	-0.0810	-0.0469	-0.1121	-0.0300	-0.1301	-0.4182	-0.3323	-0.4228
					(-0.672)	(-0.531)	(-0.308)	(-0.775)	(-0.195)	(-1.077)	(-1.170)	(-1.066)	(-1.286)
Independent Board											0.0006	0.0001	0.0005
											(0.267)	(0.073)	(0.288)
Chairman Duality											-0.2373	-0.1982	-0.2756*
											(-1.528)	(-1.445)	(-1.897)
Average Board Tenure											0.0229	0.0108	0.0142
											(1.444)	(0.789)	(0.969)
Constant	0.4643***	0.4601***	0.4625***	0.4709***	-0.0183	-0.0980	-0.0329	-0.0281	-0.0929	0.3093	-0.0171	0.0190	-0.0868
	(7.467)	(7.452)	(7.370)	(7.524)	(-0.082)	(-0.531)	(-0.143)	(-0.117)	(-0.529)	(1.607)	(-0.026)	(0.034)	(-0.154)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,079	17,079	17,079	17,079	3,641	3,641	3,641	3,641	3,641	3,641	759	759	759
Firms	1,305	1,305	1,305	1,305	427	427	427	427	427	427	99	99	99

Note: t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

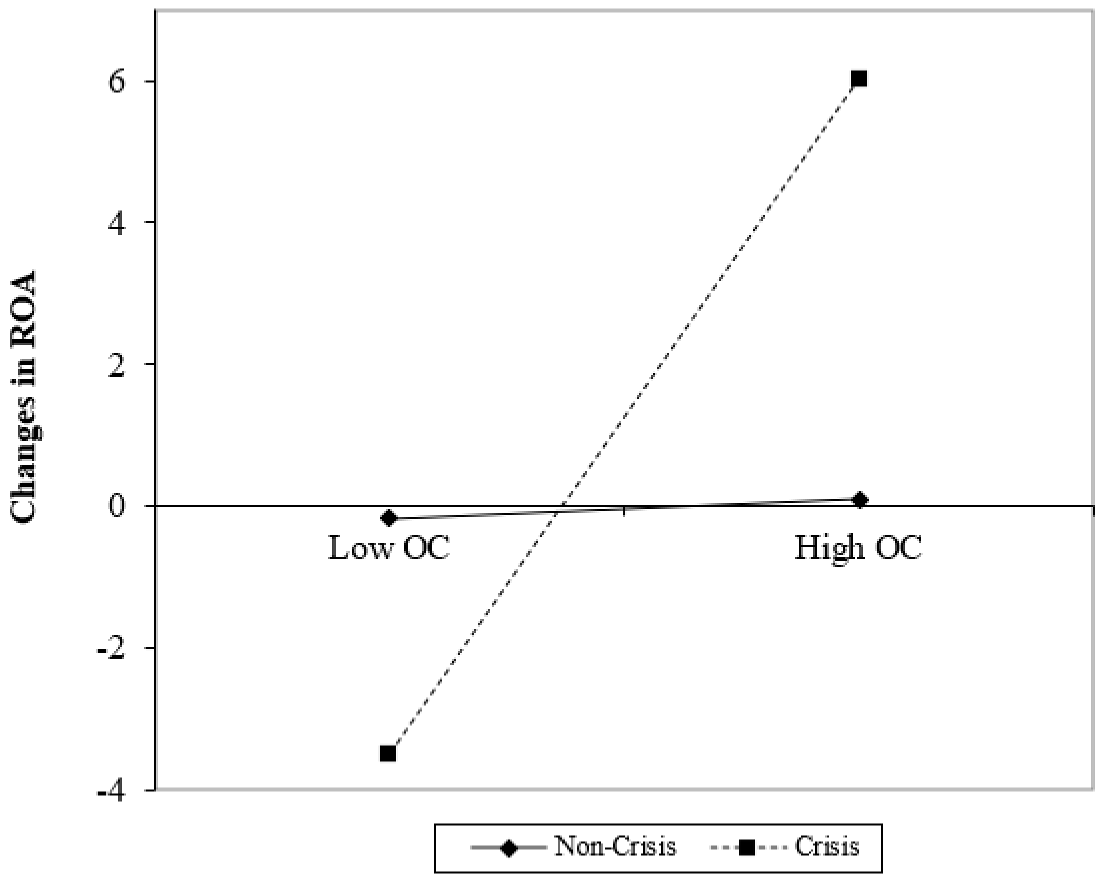
Panel B. GLS Estimates of Organisation Capital, Crisis Periods and Changes in Tobin's q

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Organisation Capital	0.3924***	0.3930***	0.4225***	0.3884***	0.2035***	0.1890***	0.1777***	0.1907***	0.1980***	0.2161***	0.2011*	0.1923*	0.3537***
	(24.477)	(23.580)	(26.284)	(24.062)	(7.633)	(6.520)	(6.114)	(6.616)	(6.567)	(6.782)	(1.790)	(1.709)	(3.133)
GFC Dummy		-0.2202***			-0.1966***			-0.2082***			-0.1028**		
		(-17.530)			(-9.402)			(-8.757)			(-2.435)		
Covid Dummy			0.1378***			0.1266***			0.1327***			0.1511***	
			(14.987)			(7.202)			(7.054)			(4.695)	
Crisis Dummy				-0.0239***			-0.0148			0.0019			0.1145***
				(-2.931)			(-1.015)			(0.122)			(4.359)
Organisation Capital × GFC Dummy								0.0700			-0.2355		
								(0.830)			(-1.035)		
Organisation Capital × Covid Dummy									-0.0336			2.3992*	
									(-0.234)			(1.759)	
Organisation Capital × Crisis Year Dummy										-0.1669**			-0.8099***
										(-2.195)			(-4.320)
Control Variables													
Firm Size					-0.0245***	-0.0255***	-0.0264***	-0.0247***	-0.0249***	-0.0263***	-0.0137*	-0.0112	-0.0189*
					(-7.042)	(-7.229)	(-7.426)	(-7.107)	(-6.884)	(-7.319)	(-1.928)	(-1.175)	(-1.910)
Firm Age					-0.0043	0.0009	0.0063	-0.0055	0.0009	0.0076	0.0086	-0.0378**	-0.0154
					(-0.461)	(0.104)	(0.686)	(-0.582)	(0.102)	(0.808)	(0.588)	(-2.127)	(-0.824)
Research & Development					0.4868***	0.4766***	0.4812***	0.4829***	0.4793***	0.4837***	0.0963	0.1321	0.1007
					(7.862)	(7.928)	(7.869)	(7.824)	(7.818)	(7.834)	(0.801)	(0.811)	(0.607)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Capital Expenditure					-0.0777	-0.0669	-0.1132	-0.0637	-0.0752	-0.1320	-0.0593	0.0617	-0.0628
					(-0.550)	(-0.477)	(-0.801)	(-0.454)	(-0.532)	(-0.928)	(-0.338)	(0.275)	(-0.264)
Leverage					-0.0914**	-0.1038***	-0.0760**	-0.0907**	-0.1032**	-0.0808**	-0.0934*	-0.2244***	-0.1477**
					(-2.347)	(-2.598)	(-1.996)	(-2.331)	(-2.560)	(-2.097)	(-1.740)	(-3.072)	(-2.107)
Independent Board											-0.0004	-0.0013**	-0.0007
											(-0.837)	(-2.411)	(-1.245)
Chairman Duality											0.0064	-0.0327	-0.0227
											(0.248)	(-0.878)	(-0.611)
Average Board Tenure											-0.0028	0.0023	0.0008
											(-1.023)	(0.608)	(0.210)
Constant	0.1131***	0.1306***	0.0978***	0.1189***	0.2314***	0.2092***	0.2144***	0.2343***	0.2088***	0.2130***	0.1940***	0.3336***	0.3054***
	(7.024)	(7.783)	(5.846)	(7.312)	(3.788)	(3.847)	(3.857)	(3.840)	(3.832)	(3.841)	(2.851)	(4.437)	(3.825)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,994	14,994	14,994	14,994	3,222	3,222	3,222	3,222	3,222	3,222	730	730	730
Firms	1,187	1,187	1,187	1,187	390	390	390	390	390	390	96	96	96

Note: t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Two-way interaction effects between organisation capital (OC) and crisis periods on Changes in ROA



We further repeat our GLS analyses by considering Tobin's q as a dependent variable to capture forward-looking firm performance. Our results are presented in Panel B of Table 4. In Panel B, we find that the relationship between organisation capital and changes in Tobin's q is positive and significant in most models, which is consistent with the relationship in Panel A of Table 4. We notice that Tobin's q decreased during GFC but increased during the recent COVID pandemic periods. As aforementioned, this could be affected by the reduction in interest rates or other factors such as digital transformation which have helped Australian firms to survive. In addition, after controlling other control and corporate governance variables, we find a positive significant effect of the interaction terms between organisation capital and Covid dummy on the changes in Tobin's q in the model (12), which reflects the positive impact of organisation capital on firm resilience during Covid period. In model (13), we find a negative and significant effect of organization capital on changes in Tobin's q during crisis periods (i.e. GFC and Covid periods together) with the inclusion of corporate governance variables. This contrasts with the positive buffering effect of organisation capital we have observed in previous analyses. A possible explanation could be the nature of different crises and measurement differences. ROA is an accounting-based measure, while Tobin's q is a market-based measure. In addition, GFC and COVID-19 are different types of crises. The GFC mainly affected the credit and financial markets, but COVID-19 affected almost every business sector. Hence, the aggregation of GFC and COVID-19 periods (i.e. Crisis dummy) could produce a different combined effect on changes in Tobin's q.

3.4 Effects of organisation capital in crisis environment

Following Osiyevskyy et al. (2020)'s study, we examine the two-way interactive effect between organisation capital and firm-specific crisis severity to understand how the interactive effects affect revenue growth during crisis periods.

Model (1) in Table 5 reports a negative standalone relationship between organisation capital and revenue growth. A higher investment in organisation capital potentially restricts funds available for other investment opportunities and thus reduces a firm's revenue growth. This remains consistent when we include Crisis dummy and control variables in models (2) and (3). Models (2) and (3) further show that firms' revenue growth decreases during the crisis periods (i.e. GFC and COVID-19 pandemic). Model (4) indicates that higher firm-specific crisis severity (as it becomes more positive) is associated with a reduction in revenue growth. We further examine whether organisation capital can act as a moderator to influence the relationship between firm-specific crisis severity and revenue growth in models (5) and (6).

The result from model (6) shows that the two-way interaction effect is negative at 10% level, indicating that organisation capital negatively moderates the association between firm-specific crisis severity and revenue growth during the crisis period. The negative relationship between organisation capital and revenue growth becomes more pronounced in firms that are more severely affected by the crisis. This shows that the magnitude of crisis or shock could potentially diminish the resilience provided by organisation capital.

Table 5: Interactive Effects of Organisation Capital, Firm-specific Crisis Severity on Revenue Growth in Crisis Environment

Following Osiyevskyy et al. (2020)'s study, this table presents the impact of organisation capital and firm-specific crisis severity on firm's revenue growth during crisis period. Firm-specific crisis severity is computed based on Eq. (4). Model (6) also presents the moderating effect of organisation capital (i.e. the interactive effect) on the relationship between firm-specific crisis severity and revenue growth.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Organisation Capital	-0.1255***	-0.1313***	-0.1980***	-0.2314***	-0.1754***	-0.2103**
	(-4.959)	(-5.081)	(-4.023)	(-3.619)	(-3.037)	(-2.103)
Crisis Dummy		-0.0900***	-0.1094***	-0.0505*	-0.0610**	-0.0155
		(-3.857)	(-3.492)	(-1.955)	(-2.382)	(-0.657)
Firm-specific Crisis Severity				-0.0528***	-0.0586***	-0.2553***
				(-10.061)	(-10.667)	(-11.523)
Organisation Capital × Firm-specific Crisis Severity					-0.0151	-0.9470*
					(-0.395)	(-1.732)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Firm Size			-0.0008	-0.0069	-0.0158**	-0.0092
			(-0.066)	(-0.836)	(-2.240)	(-1.132)
Firm Age			-0.2061***	-0.1082***	-0.0955***	-0.0179
			(-6.377)	(-4.900)	(-4.993)	(-0.959)
Research & Development			-0.0434	-0.3187***	-0.4044***	-0.2012
			(-0.290)	(-2.643)	(-3.405)	(-1.278)
Capital Expenditure			-0.2049	-0.4472*	-0.5878**	-0.2595
			(-0.582)	(-1.664)	(-2.213)	(-1.111)
Leverage			-0.3009**	-0.2597***	-0.2264**	-0.1013
			(-2.288)	(-2.719)	(-2.350)	(-1.566)
Independent Board						0.0002
						(0.296)
Chairman Duality						0.0604
						(1.199)
Average Board Tenure						-0.0036
						(-1.216)
Constant	0.3235***	0.3474***	0.8272***	0.5500**	0.5775**	0.1433
	(3.872)	(4.175)	(3.645)	(2.320)	(2.473)	(1.402)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,982	12,982	3,422	2,994	2,994	722
Firms	1,087	1,087	404	371	371	93

Note: t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

Through this Australian based study, we find a very important characteristic of organisation capital. Firms that choose to invest in organisation capital and other investments would turn out to be more productive and profitable than others. Organisation capital would help to improve changes in ROA during crisis periods if there is strong corporate governance. When interacting organisation capital and crisis, it becomes evident that their interaction could preserve firm's performance and mitigate the adverse effects during disruptive events (times), providing resilience to crisis better than the other otherwise. Despite the immediate or short-term negative impact of organisation capital on revenue growth, organisation capital could still provide the foundation for long-term resilience and post-crisis recovery, which is not captured in the current model.

As the next potential crisis will continue to impact people and businesses around the world, businesses will need to continue to prepare and respond. For countries like Australia which is filled with SMEs, it is important for them to plan the long-term investment in organisation capital to safeguard their future from the next crisis.

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THE EFFECTS OF LOCAL SHAREHOLDERS ON FIRM PERFORMANCE: EVIDENCE FROM CORPORATE SOCIAL RESPONSIBILITY

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Abstract

This paper investigates the mediating role of corporate social responsibility (CSR) in the local ownership and firm performance relationship. Prior studies provide evidence of positive effects of local ownership on firm performance. We argue that local shareholders can ensure that firms develop reputational and relationship capital through corporate social responsibility (CSR) activities that lead to higher firm performance. Our sample consists of 1,351 local mutual funds and 2,279 unique firms for the sample period of 2005-2018, for a total of 10,419 firm-year observations. Using a regression-based approach for our mediation research design, we find that the positive relationship between local ownership and firm performance is mediated by a firm's CSR activities. Our results are consistent with instrumental stakeholder theory that a firm should consider the interests of its stakeholders for strategic and instrumental reasons, primarily to enhance its long-term sustainability and profitability.

Keywords: Local shareholders, CSR, strategic intangibles, firm performance

1. Introduction

Does the geographical proximity between institutional investors and their investments affect performance? A growing body of literature discusses the economic benefits of a geographical proximity between financial institutions and their investments, such as mutual fund performance (Coval & Moskowitz, 2001), proprietary trading profits (Hau, 2001), hedge fund performance (Teo, 2009), equity analysis (Malloy, 2005), and corporate innovation (Hwang, 2023). The literature suggests that nearness to firms provides an informational edge for nearby investors over distant investors, suggesting geographical distance as a proxy for informational costs. Investors can monitor the firms effectively and obtain a better understanding of the local economy, so the information acquisition costs are relatively lower for near firms, especially firms with highly uncertain investments (Chhaochharia et al., 2012). In other words, the monitoring effectiveness and information advantages are pronounced for firms with greater investment uncertainty.

Whether corporate social investments, also known as corporate social responsibility (CSR), are associated with the increased uncertainty in firm performance is under debate (Mackey et al., 2007). CSR may help build relationships with stakeholders and improve firm value (i.e., instrumental stakeholder theory; Jones, 1995). Instrumental stakeholder theory (IST) considers CSR practices as an instrument to increase shareholder value. For example, Edmans (2011) shows a positive relation between employee satisfaction and long-term shareholder returns. Dimson et al. (2015) find that firms with successful CSR engagement experience improved performance and governance. To understand the underlying mechanisms through which CSR affects firm performance, Hasan et al. (2018) provide evidence that CSR tends to improve firm total factor productivity (TFP), thereby contributing positively to corporate financial performance (CFP). In contrast, others question the legitimacy of CSR and possible misappropriation and misallocation of scarce resources (Garriga & Melé, 2004; Margolis & Walsh, 2003). In addition, CSR may lead managers to pursue personal value, causing agency costs and deteriorating firm value (Masulis & Reza, 2015). Therefore, efficient allocation of scarce firm resources to CSR (i.e., governance, especially monitoring effectiveness) and carefully selected CSR activities to address the demands of key stakeholders (information acquisition) become crucial for firms to improve shareholder value (Porter & Kramer, 2006). Local institutional shareholders provide such monitoring effectiveness and broad information acquisition in nearby areas so that firms can effectively offer CSR to society.

This study proposes that the effective monitoring and information advantages of local institutional shareholders can help firms develop strategic intangibles such as reputational and relationship capital without incurring unnecessary costs (e.g., agency costs) regarding CSR and thus improve firm performance. Firms with higher local ownership have better internal governance and thus are more profitable (Chhaochharia et al., 2012). Better governance helps firms build their reputation, which plays a critical role in strategic marketing communications and helps win firms a competitive advantage in an increasingly crowded marketplace (Dolphin, 2004). Improved corporate reputation also increases employee retention, customer satisfaction, and customer loyalty (Chun, 2005). Shan and Tang (2023) show the positive impact of employee satisfaction on corporate productivity during Covid-19. In addition, better governance, along with CSR engagement, helps firms to reduce conflicts of interest - increase relationship capital - between managers and non-investing stakeholders (Harjoto & Jo, 2011a).

We use an extensive US mutual fund-firm dataset. Our sample consists of 1,351 local mutual funds and 2,279 unique firms for the sample period of 2005-2018, totalling 10,419 firm-year observations. Using a regression-based approach for a mediation research design, we find that local fund ownership in firms is positively related to firm performance. Geographical proximity between investors and their investments creates economic benefits because of information advantages and knowledge spillover (e.g., Coval & Moskowitz, 2001; Hwang, 2023). We also find that local fund ownership is positively related to CSR. Particularly, local funds are likely to improve environments, communities, and diversity-related social investments. Finally, it is evident that CSR mediates the relationship between local ownership and firm performance. We attribute this finding to the distinctive characteristics of local institutional shareholders, such as monitoring and information advantages when it comes to uncertain social and environmental investments. This paper sheds light on the positive impact of proximity in corporate ownership on firm performance through CSR practices.

This paper contributes to the corporate governance literature that relates ownership structure to CSR. Governance mechanisms play a critical role in CSR practices (Arora & Dharwadkar, 2011; Harjoto & Jo, 2011b). Specifically, ownership structure influences a firm's CSR activities (Dam & Scholtens, 2013; Li & Zhang, 2010; Oh et al., 2011; Oh et al., 2017). Since investors have varying preferences regarding CSR engagement, complex ownership structures create conflicts among shareholders regarding CSR (Barnea & Rubin, 2010). Local shareholders can understand their communities better and are closer to stakeholders such as employees and customers. With a strong relationship with stakeholders, local shareholders can help firms meet the needs of stakeholders more strategically. This study provides evidence that local shareholders tend to promote a firm's CSR activities, especially in the areas of environment, communities, and diversity, leading to higher firm performance.

This study also contributes to the economic geography literature that emphasises the significance of local knowledge and path dependence in economics and geography (e.g., Clark, 2018).

Geographical proximity between investors and their investments creates economic benefits because of information advantages and knowledge spillover (e.g., Coval & Moskowitz, 2001; Hau, 2001; Hwang, 2023; Kim et al., 2023; Malloy, 2005; Teo, 2009). Regulatory environments also discourage investor allocation decisions far from home (Akisik, 2020; Shima & Gordon, 2011). Leuz et al. (2009) find that foreign investments are less likely in countries with weak disclosure rules and poor shareholder protection, which decreases transparency and increases information asymmetries. However, local investors are familiar with the regulatory environment and disclosure policies, enabling them to lower information costs and monitor their firms more effectively under severe information asymmetry. The advantages of local shareholders also apply to a firm's CSR investments. This paper provides additional evidence that local shareholders promote CSR and, thereby, increase firm performance.

2. Literature Review and Theory

2.1 Local Ownership and Firm Performance

How corporate ownership structure affects firm performance dates back to Berle and Means (1932), who suggest that ownership dispersion is negatively related to firm performance. The idea is that at least some monitoring by informed shareholders is necessary to prevent agency problems, where self-interested managers undertake suboptimal decisions, a topic that has been extensively investigated in the literature (Himmelberg et al., 1999; McConnell & Servaes, 1990; Morck et al., 1988).

Previous studies suggest that local shareholders are informed and better at monitoring proximate firms since their cost of acquiring monitoring information is low relative to distant shareholders (Ayers et al., 2011; Dyer, 2021; Dyer et al., 2021). Chhaochharia et al. (2012) also find that firms with high local ownership have better internal governance and are more profitable. Finally, Hwang (2023) shows that firms with greater local ownership produce more patents and patents with a bigger impact, leading to better performance. On the other hand, the ownership structure is endogenous at best, and equilibrium ownership patterns depend on their relative costs and benefits (Demsetz, 1983; Demsetz & Lehn, 1985). Therefore, we propose our baseline hypothesis that local ownership is positively related to shareholder value (firm performance).

2.2 The Mediation Effect of CSR on the Relationship between Local Ownership and Firm Performance

That ownership structure tends to influence corporate investment and policies in various ways is based on the notion that different types of owners have divergent preferences regarding various corporate decisions and investments (e.g., Barnea & Rubin, 2010; Cho, 1998). Oh et al. (2011) document that different owners have differential impacts on a firm's CSR engagement. Consistent with previous literature, we perceive CSR as a type of investment, and different types of investors will have different effects as the social investments are the results of managerial decisions under pressure from shareholders. We argue that local shareholders play a critical role in CSR engagement. Local shareholders reside in the community where their firms operate. Husted et al. (2017) suggest that CSR activities are mainly developed close to the firm's location. Attig and Brockman (2017) also find that characteristics of local residents play a significant role in determining a firm's CSR. Therefore, we expect that the presence of local shareholders influences a firm's CSR initiatives.

Whether CSR practices help firms improve their performance is under debate (Mackey et al., 2007). Previous literature finds the relationship inconclusive, such as no relationship (McWilliams & Siegel, 2000), a positive relationship (Waddock & Graves, 1997), and a negative relationship (Wright & Ferris, 1997). On the one hand, CSR may lead managers to pursue personal value, causing agency costs and deteriorating firm value (Masulis & Reza, 2015). The argument is consistent with agency theory (Jensen & Meckling, 1976). CEO characteristics, ability, and power influence strategic decisions in CSR. Less able CEOs over or underinvest in an opportunistic way for personal benefit at shareholders' expense (Garcia-Sanchez & Martinez-Ferrero, 2019). CEOs may face pressure from institutional environments such as government regulations for CSR investments (Gupta & Chakradhar, 2022). Firms may suffer from possible misappropriation and misallocation of scarce resources (Garriga & Melé, 2004; Margolis & Walsh, 2003).

On the other hand, CSR could lead to higher firm performance. Al-Shammari et al. (2022) show that a firm's CSR is positively related to firm performance, especially for firms with high R&D and operational capabilities. This is consistent with the suggestion of Hasan et al. (2018) that CSR helps firms develop intangibles such as total factor productivity (TFP) and thereby improves firm performance. Traditional economic theories suggest that managers should pursue the best interest of shareholders, i.e., shareholder value maximisation (Friedman, 1962). Some argue, however, that maximising shareholder value is shortsighted; instead, a firm should improve stakeholder value for long-term survival and profitability (Clarkson, 1995; Freeman, 1984; Paine, 2002). Instrumental stakeholder theory (IST) provides a theoretical resolution to this conflict in that the engagement of stakeholders could also improve shareholder value (Jones, 1995). IST considers the performance consequences for firms of highly ethical relationships with stakeholders such as trust, cooperation, and information sharing (Jones et al., 2018). Garriga and Melé (2004) argue that corporations utilise CSR as a strategic tool to promote economic objectives for wealth creation. Jones et al. (2018), however, questioned why, then, the IST-based stakeholder treatment does not dominate any form of stakeholder relationship. They suggest costs associated with pursuing stakeholder relationships as a main reason. We propose that local shareholders, as effective monitors, could reduce such costs - agency costs and misappropriation and misallocation of resources - and improve firm performance.

Local shareholders are effective monitors of corporate behaviour and actively participate in firm operations through corporate governance (Chhaochharia et al., 2012; Hwang, 2023). Firms with high local ownership have better internal governance (Lerner, 1995). Consequently, managers of high local ownership firms are less likely to engage in empire building and are unlikely to enjoy the quiet life. These findings suggest that local shareholders could prevent managers from investing in CSR for their own profits and help avoid agency costs.

In addition to the monitoring effectiveness, local shareholders could have frequent face-to-face meetings with executives, visit product facilities, speak with employees, and understand the local economy better, which alleviates communication costs as well as information gathering costs (Coval & Moskowitz, 1999). With the information acquisition activities, local shareholders understand the firm's investments (e.g., CSR) better, helping managers to get required shareholder support. Finally, local shareholders are more likely to participate in community networks and spread news of the firm's social efforts and community relations. These activities by local shareholders help firms develop strategic intangibles such as reputational and relationship capital without incurring unnecessary costs (e.g., agency costs) regarding CSR. Increasing awareness of a firm's effort for community investment eventually benefits the firm financially.

3. Data and Methodology

Our empirical analysis draws upon data from various sources such as financial accounting data from Compustat, market data, and mutual fund characteristics from the Center for Research in Security Prices (CRSP), CSR data from Morgan Stanley Capital International (MSCI) ESG, and mutual fund holdings and institutional ownership data from Thomson Reuters. The Securities and Exchange

Commission (SEC) requires an institutional investment manager who exercises investment discretion over $100 million or more in Section 13(f) securities to report their holdings on Form 13F. The CRSP database is most widely used in this research field, although an omission bias problem was reported (Elton et al., 2001). Utilising MSCI ESG, we generate CSR scores founded on seven dimensions: community, corporate governance, diversity, employee relations, environment, human rights, and product. MSCI ESG assesses firms' strengths and concerns of CSR behaviours by assigning binary scores on seven dimensions (MSCI, 2015). In line with previous studies (e.g., Kotchen and Moon, 2012), we calculate a net CSR score as the sum of CSR strengths minus the sum of CSR concerns. MSCI ESG data has its own weaknesses due to changes in data collection after Kinder, Lydenberg, Domini (KLD) was acquired by MSCI, such that new KLD data are not directly comparable with historical KLD data from before 2010 (Eccles et al., 2020; MSCI, 2015). To make a net CSR measure comparable between years, we measure the standardised CSR as a net CSR for each firm per year, minus their means across firms for the same year, divided by their standard deviations (Kotchen & Moon, 2012).

To identify local institutional shareholders and their ownership in sample firms, we calculate actual distances between mutual funds and their portfolio firms based on the addresses of their headquarters. We define local institutional shareholders as mutual funds investing in a firm within 100 kilometres of their headquarters (Coval & Moskowitz, 2001). This selection process yields a final sample of 1,351 local mutual funds and 2,279 unique firms for the sample period of 2005-2018. Table 1 reports descriptive statistics for CSR and local ownership variables as well as control variables relating to firm characteristics. *Local* measures the ownership interest of local funds, while *Local/Total* represents local funds' ownership relative to overall institutional ownership. All other variables, including control variables, are detailed in Table 2.

Table 1: Descriptive Statistics

Variables	N	Mean	Q1	Median	Q3	SD	Skew	Kurt
CSR	10,419	-0.0230	-0.6221	-0.1955	0.3601	1.0149	1.5800	8.2194
Local	10,419	0.0108	0.0000	0.0000	0.0089	0.0233	3.1680	15.5381
Local/Total	10,419	0.0143	0.0000	0.0000	0.0119	0.0312	3.4380	19.5360
Tobin's Q	10,419	0.0000	-0.6503	-0.3135	0.2818	0.9996	2.1337	8.6227
Log (Size)	10,419	7.7509	6.5481	7.6321	8.8306	1.6696	0.3724	2.8868
BM	10,419	0.5101	0.2426	0.4300	0.6903	0.4183	1.4512	7.1384
Leverage	10,419	0.2550	0.0634	0.2254	0.3858	0.2205	0.8811	3.4318
ROA	10,419	0.0246	0.0083	0.0382	0.0756	0.1175	-2.8241	14.8384
|DACC|	10,419	0.1096	0.0282	0.0684	0.1422	0.1241	2.2639	9.0332
CAPEX	10,419	0.0854	0.0166	0.0323	0.0655	0.1882	5.1740	33.7881
Liquidity	10,419	14.4526	14.0440	14.4700	14.9051	0.6970	-0.3346	3.5034
Competition	10,419	-0.0713	-0.0800	-0.0511	-0.0318	0.0692	-3.3850	19.0066
Litigation	10,419	0.2247	0.0000	0.0000	0.0000	0.4174	1.3186	2.7389
Fin	10,419	0.0048	-0.0416	-0.0044	0.0226	0.1117	1.8724	10.3106
Global	10,419	0.5709	0.0000	1.0000	1.0000	0.4949	-0.2865	1.0820
IO	10,419	0.7418	0.6171	0.7989	0.9146	0.2445	-0.8056	3.9290

Table 2: Variable Definitions

Variable Names	Variable Definitions
Local	The natural logarithm of one plus the number of shares of a firm held by mutual funds located within 100 kilometres of the firm's headquarter, divided by the firm's total shares outstanding (Coval & Moskowitz, 1999, 2001)
Local/Total	The natural logarithm of one plus local ownership divided by overall institutional ownership (Coval & Moskowitz, 1999, 2001)
CSR	The standardised score of a firm's corporate social responsibility (CSR) rating, per Kotchen and Moon (2012). It is calculated as total strengths minus total concerns of CSR for each company each year, subtracting the mean across companies for the same year, and divided by the standard deviation on seven social rating categories: community, corporate governance, diversity, employee relations, environment, human rights, and product (MSCI ESG).
Size	The total assets (in millions) (Compustat AT) (Dyck et al., 2019)
BM	Ratio of book value of equity to market value of equity (Compustat CEQ/(PRCC_F*CSHO)).
Leverage	The debt-to-asset ratio (Compustat (DLC+DLTT)/AT) (Dyck et al., 2019)
Tobin's Q	The market-to-book ratio for a firm's resources, defined in CRSP/Compustat codes calculated as, (PRCC_F*CSHO+LT)/(CEQ+LT) (Dyck., et al., 2019)
OCF	Operating cash flow scaled by total assets (Compustat OANCF/AT)
ROA	Earnings before interest, taxes, depreciation, and amortisation (Compustat EBITDA), divided by the firm's average total assets (Compustat AT) (Dhaliwal et al., 2011).
|DACC|	The absolute value of performance-adjusted discretionary accruals (Kothari et al., 2005). It adds $ROA_{i,t}$ to the modified Jones model to account for the effectiveness of performance. $$\mathrm{TA}_{i,t} = \delta_0 + \delta_1\left(\frac{1}{\mathrm{ASSETS}_{i,t-1}}\right) + \delta_2\Delta\mathrm{SALES}_{i,t} + \delta_3\mathrm{PPE}_{i,t} + \mathrm{ROA}_{i,t} + \upsilon_{i,t}$$ where TA = (ΔCA - ΔCL - ΔCash + ΔSTD - Depreciation); ΔCA is the change in current assets; ΔCL is the change in current liabilities; ΔCash is the change in cash and cash equivalents; ΔSTD is the change in debt that is included in current liabilities; Depreciation is depreciation and amortisation expense; all scaled by lagged total assets. ASSETS is total assets. ΔSALES is the change in sales revenues scaled by lagged total assets. PPE is gross property, plant, and equipment scaled by lagged total assets. ROA is income before extraordinary items scaled by lagged total assets.
CAPEX	Capital expenditures scaled by total assets (Compustat CAPX/AT). (Byun & Oh, 2018)
Firm Age	The number of years since firm inception (CRSP). (Byun & Oh, 2018)
IO	Institutional ownership (Dyck et al., 2019)
Liquidity	The ratio of the number of shares traded in the year to the total shares outstanding at the year-end (Dhaliwal et al., 2011).
Litigation	An indicator variable that equals 1 if a firm operates in a high-litigation industry, defined based on SIC codes of 2833–2836, 3570–3577, 3600–3674, 5200–5961, and 7370 (Dhaliwal et al., 2011).
Competition	Equals to the Herfindahl-Hirschman Index multiplied by -1 (Dye, 1985).
FIN	The sale of common and preferred shares minus the purchase of common and preferred shares (Compustat SSTK-PRSTKC) plus the long-term debt issuance minus the long-term debt reduction (Compustat DLTIS-DLTR) scaled by total assets at the beginning of the year (Compustat AT) (Dhaliwal et al., 2011).
Global	An indicator variable that equals 1 if a firm reports foreign income (Compustat PIFO) (Dhaliwal et al., 2011).

4. Empirical Results

We first examine the association between local institutional ownership and firm performance using the following model specification:

$$Tobin's\ Q_{f,t} = \alpha + \beta Local_{f,t-1} + \gamma Controls_{f,t-1} + FE_{f,t} + \varepsilon_{f,t}, \tag{1}$$

where f and t index the firm and year, respectively. Table 3 reports the panel instrumental variable regressions with two-way clustered errors for local shareholders on Tobin's Q. This method is widely applied to panel data estimations to correct potentially biased OLS standard errors due to cross-sectional and serial correlations (Sun et al., 2018). Our measure of firm performance is Tobin's Q, which represents investors' expectations about the risk-adjusted future cash flows of a firm (Anderson & Reeb, 2003). The results show that local ownership is positively related to firm performance. The magnitude of the coefficient estimates, 1.7955 and 1.2355, suggests that a one standard deviation increase in local ownership and local ownership relative to overall institutional ownership are associated with a 4.1% and a 3.75% increase in Tobin's Q, respectively.

Table 3: The Effects of Local Fund Ownership on Firm Performance (Tobin's Q)

	Tobin's Q_t	Tobin's Q_t
$Local_{t-1}$	1.7955**	
	(2.55)	
$Local/Total_{t-1}$		1.2355**
		(2.28)
$Log(Size_{t-1})$	-0.1171***	-0.1170***
	(-16.42)	(-16.41)
BM_{t-1}	-0.9620***	-0.9618***
	(-8.34)	(-8.35)
$Leverage_{t-1}$	-0.9214***	-0.9210***
	(-10.54)	(-10.51)
$CAPEX_{t-1}$	0.1392**	0.1408**
	(2.47)	(2.51)
$Liquidity_{t-1}$	0.0686**	0.0688**
	(2.40)	(2.40)
$Competition_{t-1}$	0.3953***	0.3912***
	(2.64)	(2.62)
IO_{t-1}	-0.0869	-0.0733
	(-1.31)	(-1.14)
Cons	0.4950	0.4769
	(1.10)	(1.06)
Firm Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	10,419	10,419
R^2	0.4311	0.4310
Adjusted R^2	0.4181	0.4302

Note: The t-statistics are reported in parentheses. ***, **, and * denote significant levels of 1%, 5%, and 10%, respectively.

We also examine the association between local institutional ownership and CSR performance using the following model specification:

$$CSR_{f,t} = \alpha + \beta Local_{f,t-1} + \gamma Controls_{f,t-1} + FE_{f,t} + \varepsilon_{f,t}, \tag{2}$$

where f and t index the firm and year, respectively. Table 4 reports the results of panel instrumental variable regressions with two-way clustered errors. The coefficient estimates of Local and Local/Total are positive and significant with CSR at the 5% and 1% levels, respectively. The coefficient estimate of 0.7875 (0.7672) suggests that a one percentage point increase in local ownership raises CSR by around 78% (104%) from the mean. Our measure of local investors is consistent with Coval and Moskowitz (1999, 2001) and Hwang (2023). We define local investors as those investing in a firm within 100 kilometres of their headquarters. Coval and Moskowitz (1999, 2001) suggest a 100-km metric among several location metrics that, in most cases, are qualitatively and quantitatively similar. However, the boundary of locality could vary. Therefore, we consider an alternative local measure, *SLocal*, which is the percentage of a firm's shares held by mutual funds located within the same state as the firm (Chhaochharia et al., 2012). *SLocal* is the natural logarithm of one plus a firm's shares held by mutual funds located within the same state as the firm, divided by the firm's total shares outstanding. With the alternative measure, our results remain consistent. In Table 5, we report the empirical result of the relationship between local fund ownership and CSR components. Particularly, local funds are likely to improve environments, communities, and diversity-related social investments.

Table 4: The Effects of Local Fund Ownership on CSR

	CSR_t	CSR_t	CSR_t
$Local_{t-1}$	0.7875** (2.05)		
$Local/Total_{t-1}$		0.7672*** (2.60)	
$Slocal_{t-1}$			1.7710*** (4.26)
$Log(Size_{t-1})$	0.2481*** (6.37)	0.2483*** (6.38)	0.2463*** (6.67)
BM_{t-1}	-0.2288*** (-5.71)	-0.2280*** (-5.70)	-0.2245*** (-5.94)
$Leverage_{t-1}$	-0.4524*** (-12.48)	-0.4508*** (-12.34)	-0.4426*** (-12.96)
ROA_{t-1}	0.0332 (0.22)	0.0342 (0.23)	0.0357 (0.25)
$\lvert DACC \rvert_{t-1}$	0.3351*** (3.82)	0.3356*** (3.83)	0.3441*** (4.19)
$CAPEX_{t-1}$	-0.1759*** (-3.62)	-0.1745*** (-3.63)	-0.1405** (-3.10)
$Liquidity_{t-1}$	-0.0859*** (-3.26)	-0.0856*** (-3.25)	-0.0862** (-3.27)
$Competition_{t-1}$	0.5913*** (3.00)	0.5854*** (2.96)	0.4888** (2.39)
$Litigation_{t-1}$	0.3471*** (13.38)	0.3472*** (13.31)	0.3315*** (13.40)
FIN_{t-1}	-0.2958*** (-3.74)	-0.2970*** (-3.77)	-0.2789*** (-3.70)
$Global_{t-1}$	0.1077*** (7.62)	0.1075*** (7.64)	0.1101*** (7.74)
IO_{t-1}	-0.2528*** (-5.23)	-0.2443*** (-5.41)	-0.2553*** (-4.93)
Cons	-0.3700 (-0.86)	-0.3858 (-0.89)	-0.3922 (-0.96)
Firm Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	10,419	10,419	10,419
R^2	0.1529	0.1531	0.1519
Adjusted R^2	0.1519	0.1520	0.1519

Note: The t-statistics are reported in parentheses. ***, **, and * denote significant levels of 1%, 5%, and 10%, respectively.

Table 5: The Effects of Local Fund Ownership on CSR Components

Variable	Community	Environment	Employee relations	Human rights	Corporate governance	Diversity	Product
$Local_{t-1}$	1.1393***	1.0436***	-0.6244	-0.3049	0.7325**	0.8891***	-0.1448
	(5.22)	(2.92)	(-1.35)	(-0.80)	(-2.01)	(4.00)	(-0.56)
$Log(Size_{t-1})$	0.1299***	0.2370***	0.1747***	-0.0532*	-0.0548	0.3048***	-0.1467***
	(4.10)	(5.41)	(4.00)	(-1.96)	(-1.60)	(8.48)	(-4.84)
BM_{t-1}	-0.0821***	-0.1095***	-0.1223***	0.0350	0.0279	-0.1595***	-0.0410
	(-3.19)	(-3.09)	(-4.18)	(1.07)	(0.84)	(-5.22)	(-1.43)
$Leverage_{t-1}$	-0.2112***	-0.1443***	-0.2934***	0.0425	0.0037	-0.3612***	0.0498
	(-4.31)	(-3.09)	(-6.52)	(1.03)	(0.05)	(-11.95)	(1.44)
ROA_{t-1}	-0.1967	-0.0308	0.3476**	-0.3208*	0.1992	-0.5392***	0.1289
	(-1.75)	(-0.32)	(2.45)	(-1.70)	(1.61)	(-6.19)	(1.01)
$\|DACC\|_{t-1}$	-0.0950	0.2563*	0.4664***	-0.0603	0.0093	0.0528	0.0642
	(-0.83)	(1.84)	(7.01)	(-0.62)	(0.08)	(0.50)	(0.92)
$CAPEX_{t-1}$	-0.1960***	-0.0187	0.0867	0.1603	-0.0525	-0.1749***	0.1507***
	(-3.29)	(-0.15)	(1.02)	(1.12)	(-0.99)	(-5.98)	(3.31)
$Liquidity_{t-1}$	-0.0439**	-0.0886***	-0.0838**	-0.0174	-0.1291***	0.0562***	-0.0024
	(-2.39)	(-3.08)	(-2.39)	(-0.86)	(-2.93)	(2.66)	(-0.10)
$Competition_{t-1}$	1.3635***	0.5575**	-1.2852***	1.5545***	1.3419***	0.2831	0.9661***
	(4.33)	(2.49)	(-4.98)	(3.48)	(3.45)	(1.11)	(4.19)
$Litigation_{t-1}$	0.1887***	0.1277*	0.4411***	-0.0843***	-0.1548***	0.3448***	0.1243**
	(3.29)	(1.81)	(10.82	(-3.30)	(-5.12)	(10.76)	(1.99)
FIN_{t-1}	-0.1464*	-0.3118***	-0.2733**	-0.2351**	0.2165**	-0.2305*	0.0969
	(-1.81)	(-5.42)	(-2.21)	(-2.01)	(2.42)	(-1.95)	(1.01)
$Global_{t-1}$	0.0230	-0.0045	-0.0486*	-0.0194	-0.0596	0.0275***	-0.0002
	(0.64)	(-0.19)	(-1.81)	(-0.54)	(-1.56)	(2.82)	(-0.01)
IO_{t-1}	-0.1225**	-0.2028*	-0.1419***	0.1737***	0.0007	-0.3373***	0.1048**
	(-2.49)	(-1.85)	(-2.73)	(3.13)	(0.01)	(-3.18)	(2.42)
Cons	-0.1977	0.1420	-0.7837**	-0.8247	2.6449**	-3.0555***	0.6959
	(-0.61)	(0.27)	(-2.02)	(-1.01)	(2.53)	(-7.79)	(1.40)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,419	10,419	10,419	10,419	10,419	10,419	10,419
R^2	0.1848	0.1785	0.1291	0.0771	0.0464	0.2488	0.0937
Adjusted R^2	0.1839	0.1779	0.1308	0.0771	0.0462	0.2475	0.0931

Note: The t-statistics are reported in parentheses. ***, **, and * denote significant levels of 1%, 5%, and 10%, respectively.

We then investigate the impact of local ownership on firm performance and the mediation effect of CSR on the relationship between local ownership and firm performance. Consistent with the approach by Baron and Kenny (1986), we test the following specifications. First, we run a regression of local ownership on firm performance. Next, we estimate the effects of CSR on firm performance. Lastly, we regress both local ownership and CSR against firm performance to examine a possible mediation effect of CSR.

Table 6 reports the regression results. Columns (1) and (2) are the results of regression for the relationship between local ownership and firm performance from Table 3. Local ownership is positively related to firm performance. Column (3) shows the positive impact of CSR on firm performance, which is statistically significant at the 1% level. The coefficient estimate of CSR, 0.0722, indicates that one standard deviation increase in CSR is associated with a 7% increase in Tobin's Q. Finally, Columns (4) and (5) report the mediation effects of CSR on the relation between local ownership and firm performance. In the presence of CSR, the coefficient of local ownership is positive but statistically insignificant, suggesting that the positive impact of local ownership on firm performance is fully mediated by CSR.

Table 6: The Mediation Effect of CSR

	(1)	(2)	(3)	(4)	(5)
$Local_{t-1}$	1.7955**			1.0296	
	(2.55)			(1.60)	
$Local/Total_{t-1}$		1.2355**			0.6690
		(2.28)			(1.32)
CSR_{t-1}			0.0722***	0.0722***	0.0721***
			(4.76)	(4.73)	(4.75)
$Log(Size_{t-1})$	-0.1171***	-0.1170***	-0.1215***	-0.1215***	-0.1213***
	(-16.42)	(-16.41)	(-8.86)	(-8.98)	(-9.02)
BM_{t-1}	-0.9620***	-0.9618***	-0.9924***	-0.9905***	-0.9905***
	(-8.34)	(-8.35)	(-8.87)	(-8.27)	(-8.27)
$Leverage_{t-1}$	-0.9214***	-0.9210***	-1.0089***	-1.0270***	-1.0270***
	(-10.54)	(-10.51)	(-8.10)	(-7.95)	(-7.93)
$CAPEX_{t-1}$	0.1392**	0.1408**	0.0763	0.0797	0.0809*
	(2.47)	(2.51)	(1.04)	(1.09)	(1.11)
$Liquidity_{t-1}$	0.0686**	0.0688**	0.0541	0.0675**	0.0677**
	(2.40)	(2.40)	(1.58)	(1.98)	(1.98)
$Competition_{t-1}$	0.3953***	0.3912***	0.2287	0.1635	0.1592
	(2.64)	(2.62)	(1.09)	(0.73)	(0.72)
IO_{t-1}	-0.0869	-0.0733	-0.0197	-0.0585	-0.0441
	(-1.31)	(-1.14)	(-0.22)	(-0.63)	(-0.49)
Cons	0.4950	0.4769	0.7468	0.5465	0.5278
	(1.10)	(1.06)	(1.36)	(0.97)	(0.94)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	10,419	10,419	10,419	10,419	10,419
R^2	0.4311	0.4310	0.4139	0.4166	0.4164
Adjusted R^2	0.4181	0.4302	0.4136	0.4172	0.4165

Note: The t-statistics are reported in parentheses. ***, **, and * denote significant levels of 1%, 5%, and 10%, respectively.

Our finding of the relation between local ownership and CSR could be spurious due to endogeneity issues such as simultaneity, reverse causality, and omitted variables. To address potential endogeneity issues, first, we use one-year lagged independent variables to alleviate the reverse causality issue (Garcia-Castro & Francoeur, 2016). Second, we added firm-fixed effects and year-fixed effects following Antonakis et al. (2014). In regression analysis, omitted variable observation will be an issue if unobserved characteristics correlate with our CSR measure but are not included in the model. Firm-fixed effects, added in our model, therefore, resolve the omitted observation issue by accounting for micro-level unobservable and time-invariant heterogeneity across firms in all models (Antonakis et al., 2014). Furthermore, we added year-fixed effects to account for global economic and financial shocks and timely trends as well.

5. Conclusion

Prior studies provide evidence of an economic benefit of geographical proximity between investors and firms such as mutual fund performance, proprietary trading profits, hedge fund performance, and equity analysis, especially a positive effect of local ownership on firm performance due to greater corporate innovation and better internal governance. This paper uncovers the impact of local institutional shareholders on firm performance by investigating the mediating role of corporate social responsibility (CSR) in the local ownership and firm performance relationship. We argue that the monitoring effectiveness and information advantage of local shareholders can ensure that firms develop reputational and relationship capital through corporate social responsibility (CSR) activities that lead to higher firm performance. Consistent with our expectation, higher local ownership results in greater CSR investments and, thereby, increases firm performance. Our results are consistent with instrumental stakeholder theory that a firm should consider the interests of its stakeholders for strategic and instrumental reasons, primarily to enhance its long-term sustainability and profitability. The findings suggest that better governance and greater information regarding stakeholders could not only improve a firm's reputation and relationships with stakeholders through CSR but also help benefit firm performance. Finally, our study acknowledges some limitations related to US-specific data. Differences in institutional environments at the country level and globally diversified portfolios may impact a firm's CSR policy.

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THE IMPACT OF SOCIAL MEDIA PRESENCE, RESPONSE TIME, CORPORATE ACTIONS ON THE STOCK MARKET: EVIDENCE FROM THE RUSSIA–UKRAINE WAR

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Abstract

This study investigates the influence of social media presence and conflict response on the stock returns during the Russia–Ukraine war. We examined the long-term impacts regarding social media presence, response time, action taken using a sample of 174 firms in 10 industrial sectors. The results highlight that response time and corporate actions significantly impacted stock returns in both the short- term and long-term. Conversely, social media presence marginally affected response decisions, but did not affect stock returns.

Keywords: Russia-Ukraine conflict, Stock Returns, Social Media

1. Introduction

The outbreak of wars oftentimes significantly affects stock market performance in both the short and long term (Collier & Hoeffler, 2004). These conflicts increase the vulnerability of the global supply chain, leading to rapid and unpredictable fluctuations in prices. Beyond the immediate impact on price dynamics, these wars can trigger disruptions to the worldwide supply, influencing economic and trade structures. To this extent, researchers have evaluated that the conflicts can generate higher market volatility, indicating a negative relationship between conflict and stock market stability (Lehkonen & Heimonen, 2015). The far-reaching consequences extend to the reshaping of global political and economic patterns over the long term.

The Russia–Ukraine conflict, which began on February 24, 2022, has had far-reaching consequences for geopolitics and the global economy. Two key areas that this conflict affects are the European financial market and the global commodity market (Umar et al., 2022). With countries still recovering from COVID-19, the aftereffects of the Russian invasion are likely to have a compounding financial effect. Given the strategic importance to the economy of the affected natural resources and commodities, the implications for inflation and supply chain disruption are yet to unfold. Earlier findings from a study spanning 40 countries' stock markets indicate that Russia-Ukraine conflict had anticipatory effects, days prior to the event, on neighbouring markets in Hungary, Poland, Serbia, Bosnia and Herzegovina, and the Czech Republic, with reduced volatility observed in distant and primary markets in USA, UK, and Japan. Furthermore, volatility decreased as war-related information surfaced (Gheorghe & Panazan, 2023). The conflict in Ukraine has caused substantial volatility in the energy and agriculture sectors resulting in rising prices (Fang & Shao, 2022). The researchers further identified these markets as the most sensitive to conflict, exhibiting significant interconnections, notably observed through pronounced spillovers between metal and energy markets. Using a difference-in-differences model to explore market divergency, the study in Clancey-Shang & Fu (2023) finds that foreign stocks listed in the US as a whole experience more significant market quality deterioration compared to their domestic counterparts, with the spillover effects disproportionately impacting foreign firms in the US stock market. Together, it showed that time sensitivity and sector matter to the market in a conflict. Hence, we are motivated to fill the gap from earlier research, which fell short to specify the reaction of identified interests' group, further to a long-term effect in the extent of responding actions by the event, other than an aggregation of entire market performance.

Many international businesses have decided to leave or temporarily shut down their operations in Russia owing to public demand (Basnet et al., 2022). Prior research has analysed these corporate decisions and their immediate impacts on equity markets, suggesting that the companies that remained in Russia underperformed greater than those leavers and their market benchmark (Tosun & Eshraghi, 2022). However, the corporate decision to maintain its regional business may also collide with the pushback of social pressure (DiNapoli & Naidu, 2022). The survey results then of a Morning Consult Survey conducted in February 2022 showed that 37% of US respondents supported cutting business ties permanently and stopping sales of products and services in Russia, whereas merely 8% stated that companies should maintain their Russian business but issue a condemning statement (Case, 2022). That makes the involved company a difficult decision.

The actions of leaving, temporarily stalling, or continuing operations in Russia varied across companies from different sectors in the US. For instance, focusing on two unique industries, a prior study finds the war had a significantly negative impact on the airline market but a positive effect on the defence market (Le et al., 2023). We articulate that key corporate actions facing a dilemma have followed the social pressure (DiNapoli & Naidu, 2022), including from the competitive peer, and incorporated the best interests on the global operations to formulate the decisions. Our first research question (RQ1) further evaluates the relationship between the industrial sectors and the type of corporate actions taken in response to the conflict.

RQ1: Is there an association between the industrial sector and the type of corporate action responding to the Russia–Ukraine conflict?

The responses of numerous industries to other crises, such as natural disasters, the COVID-19 pandemic, and the recent Russia–Ukraine conflict, highlight their need for more preparedness for extreme situations. According to Gaio et al. (2022), while the war has impacted the market efficiency in developed countries, it has not reached the same magnitude as the COVID-19 pandemic. Our following research question investigates how a company's decision, and the timing of its announcement relate to the stock market's volatility, which is linked to Gaio et al.'s (2022) findings regarding the impact of war on market efficiency. It is noted by above mentioned research that the war has affected market efficiency, whereas impacts on the global economy will be inevitable if the war becomes long (Gaio et al., 2022). This insight, mainly based on the market efficiency theory, underscores the broader economic context for companies to the extent of their long-term performance. Exploring how companies respond to geopolitical uncertainties amid discernible market impacts becomes relevant. Our next research question builds upon Gaio et al.'s (2022) acknowledgement of geopolitical event's impact on market conditions, aiming to understand how companies manage and when they respond to the war conflict, potentially influencing stock market performance.

RQ2: Do companies' response time and the type of action affect their stock returns?

Unexpectedly, the war continues and stretches its length than previously expected. Our study remains relevant and provides managerial implications to investors, corporate executives, and offers evidence to the line of financial market study on the geopolitical tension and crisis. Our research endeavours to address the long-term impact of the conflict on the stock market performance and contribute to the existing literature that primarily focuses on the short-term effect. In a similar vein, future studies may explore the social media presence, corporate response, and the long-term effect to the developing crises surrounding the Middle East region.

Companies often use social media for the purpose of customer engagement to promote and improve brand trust and loyalty within the community (Seller & Laurindo, 2018). Further, social media platforms are a meaningful communication channel between customers and companies. Similarly, companies may be pressured by the public sentiments of social media and may respond to certain decisions based on the requests of potential customers and the public. The following research question aims to evaluate whether the companies' social media presence, like the number of tweets in a week and Twitter followers, affects their decisions related to the Russia–Ukraine war.

In addressing the above discussion concerning the impact of social media presence on companies' actions and corresponding response times on decision during the Russia-Ukraine conflict, we have "social media presence" denotes the degree of a company's visibility and engagement across social media platforms, with a particular emphasis on Twitter. Response times are measured by counting the days from the beginning of the conflict to the moment a company issues the statement. This presence has the potential to shape the way companies communicate, respond, and formulate decisions amidst political challenges such as the Russia-Ukraine conflict. We therefore first form the research question as follows.

RQ3: Does social media presence affect companies' action and response time during the Russia-Ukraine conflict?

Unexpectedly, the war continues and stretches its length than previously expected. Our study remains relevant and provides managerial implications to investors, corporate executives, and offers evidence to the line of financial market study on the geopolitical tension and crisis. Our research endeavours to address the long-term impact of the conflict on the stock market performance and contributes to the existing literature that primarily focuses on the short-term effect.

2. Data and methods

Similar to Glambosky and Peterburgsky (2022), we used Yale's School of Management data collected on May 1, 2022, (https://som.yale.edu/centers/chief-executive-leadership-institute)to examine the companies and their involvement in activities related to the Russia–Ukraine war for our analyses (Sonnenfeld et al., 2022). Furthermore, we incorporated information on the companies' presence on Twitter and the dates of their action announcements, which were retrieved as of June 30, 2023. The dataset used were then manually verified. To operationalise and capture the social media presence, we integrated two key independent variables: the frequency (by the number of weekly tweets) and exposure on Twitter (by the number of Twitter followers)[1]. To measure corporate actions, we have the type of action as a categorical variable with the following values: Holding Off (0), Partial Suspension (1), Temporary Suspension (2), and Complete Suspension (3). The response time is calculated by the number of days that elapse from the start of the conflict until a company releases a statement. Additionally, the industrial sector of each firm is another variable considered in our analysis, as detailed in Equation 1. The company's industrial sector, along with the days

[1]It is noted that the social media presence data has been compiled from the official Twitter accounts of various organizations in our study. The number of followers, representing people interested in updates from these organizations, is expressed in thousands, and we have also recorded the average weekly tweets from each account. For those without an official account, a default value of "0" has been used.

elapsed since a decision was made, are the key variables of interest in our study. As a result, our sample consisted of 174 firms spread across 10 industrial sectors. The following regression model is used to examine the research questions.

$$\text{Returns} = \beta_0 + \beta_1 \text{ Response Time} + \beta_2 \text{ Action} + \beta_3 \text{ Tweets} + \beta_4 \text{ Twitter Followers} + \beta_5 \text{ Sectors} + \varepsilon \tag{1}$$

Table 1: Summary of the different actions across 10 industrial sectors

Industrial Sector	Action			
	Holding Off	Partial Suspension	Temporary Suspension	Complete Suspension
Communication Services	4	1	3	4
Consumer Discretionary	5	4	5	10
Consumer Staples	1	6	6	5
Energy	0	2	1	1
Financials	3	0	2	3
Health Care	1	6	5	1
Industrials	12	1	10	11
Information Technology	15	0	6	29
Materials	3	1	1	1
Real Estate	3	0	0	2

Notes: Table 1 provides descriptive statistics on the levels of suspension that companies have released public statements on Twitter and major news platforms by industrial sectors. The information technology (IT) sector has been greatly affected, with the highest numbers across all suspension categories. It had the highest counts in terms of Holding off (15), Partial Suspension (0), Temporary Suspension (6), and Complete Suspension (29), suggesting a significant disruption in the IT firms compared to the others.

Table 2: Descriptive statistics of sample firms on social media presence across the sectors

	Followers (in thousands)						
	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
Communication	7854.84	254.79	18740.54	10.16	3.13	0.59	65550.99
Consumer -Discret	37.82	0	104.93	5.92	2.65	0	376.74
Consumer -Staples	175.79	0	737.35	17.99	4.24	0	3130.17
Energy	42.91	50	31.26	-0.33	-0.96	1.16	70.47
Financials	78.51	0	206.72	7.89	2.81	0	589.01
Health Care	38.28	0	88.97	3.31	2.18	0	250.51
Industrials	70.44	0	292.23	28.93	5.27	0	1663.81
Info Technology	7.94	0	34.31	30.99	5.42	0	218.01
Materials	7.67	2.05	13.63	5.12	2.23	0	34.91
Real Estate	0	0	0	0	0	0	0

Average Weekly Tweets							
	Mean	**Median**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
Communication	75.33	46.5	103.71	5.67	2.22	0	364
Consumer-Discret	424.46	49.5	655.86	2.01	1.71	0	2211
Consumer Staples	40.28	27	38.93	-0.46	0.88	0	120
Energy	3.5	0.5	6.35	3.88	1.97	0	13
Financials	86.75	38.5	126.49	7.42	2.69	24	396
Health Care	22.077	13	30.26	5.79	2.32	0	109
Industrials	260.79	18	633.55	5.94	2.67	0	2328
Info Technology	96.2	48	151.31	9.56	2.99	0	747
Materials	11.33	10.5	7.42	1.85	0.11	0	23
Real Estate	44	21	62.12	3.53	1.86	0	151

Notes: The summary statistics in Table 2 reveal that companies in real estate have the least followers, which could be attributed to their lower activity levels, or limited public interest to this sample group. The great differences in the values of maximum, mean, and minimum suggest wide variability in a skewed distribution across sectors. The Communication Services sector boasts the highest number of followers, due to the presence of major companies like Meta, Google, and X Corp(formerly Twitter). Companies in this sector are also the most active on Twitter. The Consumer Discretionary sector, including McDonald's, Pizza Hut (Yum! brands), and Amazon shows the highest average number of tweets for robust engagements. On the other hand, the IT and Communication Services sectors rank as the second and third most active, correlating with their strong engagement metrics. The Energy sector is the least active on Twitter, targeting a niche audience rather than the public, and preferring to communicate through other channels. This approach reflects the respective but rather specific audience engagement strategy, which does not rely heavily on social media.

Table 3: Descriptive statistics of social media presence across suspension categories

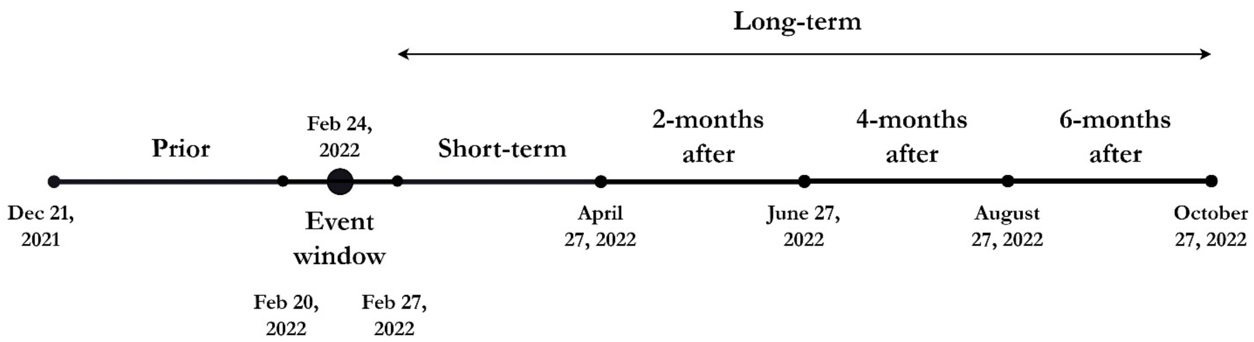
Followers (in thousands)							
	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
Holding Off	24.57	0	71.58	7.44	2.93	0	250.51
Partial Suspension	102.87	0	503.62	36.99	6.03	0	3130.17
Temporary Suspension	11.13	0	37.38	21.5	4.41	0	218.01
Complete Suspension	67.16	0	262.11	31.36	5.35	0	1663.81
Tweets							
	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
Holding Off	84.76	21	244.25	19.85	4.41	0	1138
Partial Suspension	60.67	24	128.53	22.71	4.53	0	747
Temporary Suspension	172.58	28	428.43	12.94	3.57	0	2328
Complete Suspension	226.28	25	535.39	9.66	3.19	0	2303

Notes: Table 3 depicts the descriptive statistics of social media presence across suspension categories. There are substantial differences in follower counts among companies wherein the Partial Suspension category reports the highest variability and skewness in Followers, mainly due to a small sample observation (21) in the group. For Tweets, companies classified under Complete Suspension have the most active Twitter engagements, suggesting that higher Twitter activities could be associated with decisions to completely suspend operations. The median value of zero for Followers across all categories indicates that many companies have negligible or no followers on their official Twitter handles, highlighting the limited significance of this metric in broader analyses. However, the variability in tweet counts across different groups, especially those announcing Complete Suspensions, suggests notable differences in Twitter activity levels among companies.

3. Results

A chi-square test was conducted to determine whether there is an association between the type of industry and the company's decision on the responding action (RQ1). The results showed a significant relationship between them, with a p-value of 0.0012. Moreover, it is further evident from Table 1 that most companies in the consumer discretionary (41.67%) and IT (58%) sectors have taken drastic measures by announcing their Complete Suspension.

Figure 1: Event window and time-period selection for regression analysis



We employed the regression analysis in Eq 1 to evaluate how actions and response time affect stock returns (RQ2). We used data from December 21, 2021, to October 27, 2022, as shown in Figure 1, to address the temporal effect. Regarding the conflict between Russia and Ukraine, the significant date we pinpoint is February 24, 2022, marking the onset of hostility with Russia's initial military incursion into Ukraine. The window was then extended to include the three days leading up to the military action (February 20) and the three days after the announcement (February 27). Following a similar method that Gaio et al. (2022) applied in prior event period, our first analysis involved the following periods: prior (December 21 – February 20), short term (February 27 – April 27), and long term (February 27 – October 27).

Table 4: Regression results in the time periods: prior, short term, and long term

	Prior	Short Term	Long Term
Response Time	-	0.1539***	0.2221**
Industry	0.7387***	0.705	0.1821
Action	-	-1.8196**	-4.7862**
Tweet Count	0.0004*	0	-0.0002
Followers	0	0	0.0003
R^2 (within)	0.092	0.102	0.051

Notes: *, **, *** indicate the significance at the 0.1, 0.05, and 0.01 level, respectively.

The regression results in Table 4 provide insights into the relationship between the variables of interest and stock returns across different time periods. Regardless of the short-term and long-term periods, the response time shows a positive and significant association with the stock returns. Companies that have taken full consideration of business interests in aspects of global operation, responding to the critical withdrawal decision by observing the conflict development and taking the necessary time to prepare, were rewarded with overall high returns. That contrasts with companies in a brisk consideration of critical decision seeking immediate action in a short period exhibited lower returns. The notion is consistent in the finding that the actions taken by the companies have a notable adverse effect in both short-term and long-term, in which the market was not in favour of the companies moving toward a Complete Suspension of operation.

Interestingly, empirical evidence from the above indicates that market participants reacted differently from the public opinions surveyed at the start of the conflict (Case, 2022). However, Industry affiliation demonstrates a positive and significant influence before the conflict. The results resonate with the implication of anticipation effect prior to the conflict in Gheorghe & Panazan (2023). The shift in the capital market, from a focus on industry sensitivity to the post-conflict corporate response time and action decision, indicates that subsequent announcements play a larger role in influencing the fluctuations of stock returns compared to the industry sector.

Researchers investigating U.S. firms that withdrew from Russia reported generally stable stock returns shortly after their announcements (Balyuk & Fedyk, 2023; Sonnenfeld et al., 2022). These prior studies noted minimal immediate financial impact and even a stock price increases for some firms within a week of their exit announcements. However, when examining the broader consequences of these decisions over periods of 2 months and 6 months, a significant decline in stock returns was observed. This downturn could be attributed to the gradual fading of the initial ethical and reputational boost, leading investors to focus on the fundamental losses from the Russian market exits. This reassessment of future revenue and profitability might explain the observed decrease in stock value. These findings align with other research, which also noted negative stock returns following such decisions (Ayoub & Qadan, 2023).

In addition, the number of tweets shows a marginally significant positive effect in the prior period while not being pronounced overall in the short- and long-term after the conflict. The reason could be that specific sectors may be less influenced by social media due to the nature of operations in sample groups, or susceptible to Twitter for statements. Our findings on the diverse impacts of social media presence align with early research by Huang et al. (2014) and Shi et al. (2022), which both demonstrate that investor sentiment has varying effects across different industries. Similar findings have been observed by other studies, which assessed the relationship between social media attributes and stock returns, corroborating the notion that investor sentiment significantly and variably affects different sectors (Niu et al., 2023; Rehman et al., 2021; Sayim et al., 2013). Overall, the results above reveal that our study in long-term market returns presented different findings from those in prior related literature conducting event studies with a relatively short window, such as in Tusun & Esraghi (2022).

The effect of social media presence on the firm’s decisions (RQ3) was tested using ANOVA (analysis of variance), and the results indicated that the relationship is not supported in a statistical significance (p-value = 0.2889). That implies that variations in social media presence, particularly within the parameters tested, are not a determining factor influencing the decisions made by the investigating firms. The impact of social media presence on the timing of companies’ decision to announce was tested using the regression analysis, and similarly the results indicate that the relationship is not supported in a statistical significance (F-stat = 0.4526) as seen in Table 5 below.

Table 5: Regression results for RQ 1 (Followers and Weekly tweets – Independent variable and Response Time-Dependent variable)

Model	Standardised coefficients	t-statistic	p-value
Followers	-0.12	-1.485	0.14
Weekly Tweets #	-0.028	-0.35	0.727

Table 6 summarises the Cumulative Abnormal Returns (CAR) regression analysis results across industrial sectors in the short term. The Energy, Materials, and Real estate sectors have few observations and, therefore, are excluded in the above analysis. Financial markets respond keenly to real-time updates and higher tweet counts in the short term, shaping investor sentiment due to the business nature of required immediate responses and rapid changes in this Finance sector. In Healthcare, the market also reacts positively to a prominent social media following for immediate concerns about the medication and drug shortage in the war zone. More followers mean the attention of a larger audience exposed for a company's announcements, updates, and positive news. This increased visibility can attract more investors and positively influence stock prices.

Table 6: Short-term CAR regression results across the industrial sectors

	Financials	Consumer Discretionary	Communication Services	Consumer Staples	Health Care	Industrials	Information Technology
Observations	8	24	12	18	13	34	50
Response Time	0.9008	0.1194	-0.5584	0.4175	- 13.1369	0.0747	0.2442
Action	-20.9578	-6.4098	-10.9623	-2.5059	0.0432	2.4280	-5.3823
Tweet Count	0.0237	0.0005**	-0.0217	0.2396	0.2315	-0.0102	0.0111
Followers	0.0247***	0.0015	0.0009	-0.0042	0.1267*	0.0061	-0.0002
R^2 (within)	0.954	0.171	0.412	0.324	0.406	0.542	0.954

Notes: *, **, *** indicate the significance at the 0.1, 0.05, and 0.01 level, respectively.

Further, a high tweet count in the Consumer Discretionary sector is positively associated with CAR. This suggests that companies in this sector, with an increased frequency of tweets, may experience higher-than-expected stock returns. The correlation implies that active and engaging communications on social media platforms, critical to this type of direct end-users-oriented business nature, could contribute to positive investor sentiment and improve financial performance within the Consumer Discretionary industry.

Investors in various sectors may have distinct decision-making criteria and preferences for information sources. In addition, each industry has unique characteristics, risk profiles, and market behaviours. Another factor might be that firms identified based on the announcements in the US may not have been notably affected by the Russia-Ukraine conflict. Some sectors may be less susceptible to social media influence due to the nature of their operations or the type of products and services they offer. We could not completely exclude the possibility and limitation of the inherent randomness of the stock market (Delgado-Bonal, 2019; Malkiel, 2003).

Moreover, our additional analysis results (untabulated) suggest that the "Tweet Count" variable positively correlates with the stock returns of companies that have temporarily withdrawn from Russia, pointing out that the market responds well to rapid action under social pressure. However, it does not exhibit a similar pattern for the other decision categories. Overall, the findings imply that social media presence has a noteworthy influence on the action decisions and within specific industries in the short term, as observed in Table 4.

4. Conclusion

The findings suggest that companies must consider their social media presence and engagement with their audience in specific industries such as Financials, Consumer Discretionary, and Health Care. While the overall impact on company decisions may not be significant, the number of tweets can have a marginally positive effect in specific periods. The analyses demonstrate that industry affiliation substantially impacted company decisions before the start of the conflict, as some sectors were more sensitive to the continuous development of the business environment that led to the outbreak of war. The actions taken by companies during the conflict significantly affect stock returns. Different levels of action, such as Partial or Complete Suspension, can influence investor sentiment and stock performance.

Further, we reveal another finding that is essentially considered in corporate response time. It suggests that companies responding briskly, without the necessary time to consider the global operations reported lower returns. In contrast, those taking more extended time in complete consideration responses to conflicts exhibited higher stock returns. This unique decision for wartime crises contradicts the conventional notion that a quicker response mitigates damage. We caution against the interpretation that the result is based on an analysis focusing on a small set of companies explicitly addressing this conflict. A broader examination involving diverse global markets and evaluations of responses to different conflicts may be warranted. The lack of statistical significance in tweet counts may stem from the absence of activities by some firms across different suspension categories, resulting in indistinctive patterns of differentiation.

The analysis primarily examines how stock returns are influenced by social media presence, corporate response time, and action taken. However, it is essential to acknowledge the research limitations that various external factors, including macroeconomic conditions, market sentiment, and geopolitical events, can also affect a firm's stock returns. While the analysis considers these factors, it is worth noting that the ongoing conflict introduces additional complexities and dynamics that may need to be fully captured within the selected time frames or during the relevant events.

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Appendix

Table A.1: List of companies

Alcoa	McDonald's	Mohawk Industries
AECOM	Marsh McLennan	Merck
Ametek	Moog Inc.	Manitowoc
Avid	MSCI	Nature's Sunshine
Avery Dennison	Norwegian Cruise Lines	National Oilwell Varco
Ball Corporation	Nike	Pfizer
BBDO	Netscout	Procter & Gamble
BlackRock	Owens Corning	Schlumberger
Bumble	Omnicom Media Group	Vimeo
Cadence	PGL Esports	Weatherford International
Carnival	Parker Hannifin	Align Technology
Cummins	Pentair	Fleetcor
Coty	PwC	Huntsman Corporation
Salesforce	Roku	Aimbridge | Interstate Hotels
Cisco	Starbucks	International Paper
Cushman & Wakefield	Sonos	IQVIA
Delta Air Lines	State Street	Lear Corporation
DDB	Stanley Black & Decker	Medtronic
Krispy Kreme	Teradata	Match Group
DXC Technology	TripAdvisor	Cloudflare
Electronic Arts	edX (2U)	Stryker
Emerson Electric	Uber	Riot Games
EPAM	Universal	Tenneco
Vanguard	WeWork	Tupperware
Etsy	Wex Inc.	Titan International
Exxon	Abbvie	Zimmer Biomet
Expedia	AmerisourceBergen	Adobe
FICO	Abbott Laboratories	AGCO
Flowserve	Archer Daniels Midland (ADM)	Amgen
FMC Corporation	Arconic	Activision Blizzard
GoDaddy	Bristol-Myers Squibb	Avaya
Grid Dynamics	Colgate-Palmolive	Bunge
Global Foundries	CAPRI Holdings (Versace, Michael Kors, Jimmy Cho)	BNY Mellon
HP Inc.	Domino's Pizza	Boston Scientific
IBM	Greif	Carrier
Intercontinental Exchange	GXO Logistics	Caterpillar
IDEXX Labs	Hyatt	Coinbase
Interpublic Group	Hilton	Carter's | Oshkosh
Jabil	Johnson & Johnson	Donaldson Company
JLL	Kraft Heinz - JBS	Deere
Kelly	Kimberly-Clark	Dover Corporation
Koch Industries	Eli Lilly	Dow
Lincoln Electric	Mondelez - Nabisco	Duolingo
Lamb Weston		Elanco

Eaton
Fortive
GE
General Mills
Corning
Alphabet
Gap Inc
Garmin
Goldman Sachs
Halliburton
Herbalife
IPG Photonics
JPMorgan
Kellogg
Coca-Cola
Kearney
Loyalty Ventures
Mars
Moody's
Microsoft
NielsenIQ
Okta
Otis Worldwide
Phibro Animal Health Corp
Paccar
Pepsi
Philip Morris
PPG
Sabre
Signet Jewelers
Sketchers
Shutterstock
Terex Corporation
Tennant
Ingersoll Rand
Westinghouse Air Brake Technologies Corp
Whirlpool
Yum! Brands
Zoetis
American Airlines
Apple
Airbnb
Analog Devices
ADP
Autodesk
Akamai
Alaska Airlines
Ambarella

AMD
Amazon
Ansys
American Express
Boeing
BCG
Brown-Forman
Booking
Baker Hughes
B Lab
Bentley Systems
Citi
CBRE
Cogent Communications
Conformis
Ciena
Clorox
CME Group
Columbia Sportswear
Costco
Coupa
Coursera
Crocs
Citrix
Chevron
Diebold Nixdorf
DuPont
Deckers
Dell
Danaher
Disney
Amdocs
eBay
Estee Lauder
Equinix
Ford
FedEx
Fortinet
GM
Goodyear
Hasbro
Harley-Davidson
Honeywell
Intertek
Intel
Intuit
Illinois Tool Works
Juniper Networks
Korn Ferry

Levi Strauss
Lumen
Live Nation Entertainment
Mastercard
Marriott
Mattel
MongoDB
Meta
McCormick
3M
Marvell
Motorola Solutions
MSC
Micron
NCR
NetApp
Nutanix
Nu Skin
Nvidia
ON24
Oracle
Par Pacific
UiPath
Payoneer
PagerDuty
Paramount
Polaris
PTC
PVH
Paypal
Papa John's
Qualcomm
Burger King (Restaurant Brands)
Royal Caribbean Cruises
Remitly Global
Ralph Lauren
Rockwell Automation
Raytheon
Sylvamo
Synopsys
Timken
Thermo Fisher
Trimble
Take-Two Interactive
Twin Disc
Twitter
Under Armour
United Airlines

UL
UPS
Upwork
Visa
VF Corporation
Valero Energy
VMWare
Victoria's Secret
Waters Corporation
Western Union
WWE
Xerox
Zendesk

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POWER OF CSAD-BASED TEST ON HERDING BEHAVIOUR

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Abstract

This study aims to answer the question of whether the cross-sectional absolute deviation (CSAD)-based test is powerful enough to detect herding behaviour in financial markets. Using US stocks as the main sample, I investigate the power of the CSAD-based test as a herding detection method, with a focus on two dimensions: the self-consistency of the method and the power of t-tests used in the method. I find that conducting the tests with a large number of stocks over extended time periods is likely to provide consistent conclusions on whether herding behaviour exists in the stock market. These findings support the CSAD-based test as a herding detection method. However, with an overall mean of 59.37%, the estimated power of t-tests can be as low as 37.62%, indicating low testing power. Therefore, researchers should be careful when using the CSAD-based test as a herding detection method, especially when $\boldsymbol{R}^2$s are low.

Keywords: herding behaviour, CSAD-based herding detection method

1. Introduction

Since Chang et al. (2000) proposed the herding measure based on cross-sectional absolute deviation (CSAD), researchers have used this method to study herding behaviour worldwide. As a result, it has been determined that herding behaviour exists in different financial markets around the world. The CSAD-based method has a strong theoretical framework built on the capital asset pricing model. However, features of this method have not been fully discussed in the literature. Of the undiscussed features, the power of the herding tests is a significant one. The power of herding tests can be decomposed into two dimensions: the self-consistency of the method and the power of t-tests used in the method.

Table 1 below outlines selected research studies in which the CSAD-based method was used to detect herding behaviours and summarises the sample used in each study. The sample size ranges from 6 to 912. The first question to consider is whether a sample of 6 and a sample of 912 form consistent conclusions on herding behaviour under similar market conditions. If not, then it is important to determine how many stocks should be considered for the studies. Ideally, the results obtained through the CSAD-based method should exhibit convergence towards a stable level as the stock sample size increases. However, there is a lack of evidence to support this expectation. This raises concerns about the method's accuracy and reliability when samples of different sizes lead to different conclusions regarding herding behaviour under similar market conditions.

Table 1: Sample of Selected Studies Using CSAD-Based Methods

Article	Target market(s)/area(s)	Sample size	Sample period	Data frequency
Espinosa-Méndez and Arias (2021)	Stock markets in France, Germany, Italy, the United Kingdom, and Spain	30 to 100	January 3, 2000, to June 19, 2020	Daily
Yarovaya at el. (2021)	USD, EUR, JPY, and KRW cryptocurrency markets	6 to 12	January 1, 2019, to March 13, 2020	Hourly
Bernales et al. (2020)	US equity options market	-*	January 1996, to December 2012	Daily
Youssef and Mokni (2018)	Stock markets in six Gulf Cooperation Council countries	-*	January 5, 2003, to May 28, 2017	Weekly
Kabir and Shakur (2018)	Stock markets in eight Asian and four Latin American countries	171 to 912	January 1, 1995, to December 31, 2014	Daily
Pochea et al. (2017)	Central and East European stock markets	9 to 331	January 2, 2003, to December 31, 2013	Daily
Philippas et al. (2013)	US REIT market	112 to 152	January 2004, to December 2011	Daily
Economou et al. (2011)	Portuguese, Italian, Spanish, and Greek stock markets	49 to 337	January 1998, to December 2008	Daily
Chiang and Zheng (2010)	Stock markets in 18 countries	53 to 155	May 25, 1988, to April 24, 2009	Daily
Tian et al. (2008)	Stock market and its submarkets in China	54 to 746	July 12, 1994, to December 31, 2003	Daily, weekly, monthly

*No sample size is specified in the studies.

The sample periods are also critical. Most articles listed in Table 1 have sample periods of more than 10 years. For example, Bernales et al. (2020) used the CSAD-based method to study a daily dataset spanning from January 1996 to December 2012 and provided approximately 4,215 daily observations. Conversely, Youssef and Mokni (2018) evaluated a weekly dataset and offered approximately 751 weekly observations. In theory, more observations are associated with higher testing power, which raises the question of whether 751 observations are sufficient.

Another open question concerns the power of the t-tests used in the method. The power of the t-tests directly impacts the power of the CSAD-based method, setting the upper bound of its testing power. However, previous studies show little regard for the statistical power of tests in the field of finance. Kim and Jin (2015) conducted a survey on 161 articles published in four journals, Journal of Finance, Journal of Financial Economics, Journal of Financial and Quantitative Analysis, and The Review of Financial Studies, in 2012 and found only one article discussing the power of tests. None of the previous works discuss the statistical power of the CSAD-based method. In this study, I address these gaps in the literature and provide insights into the unanswered questions.

The remainder of this study is organised as follows: Section 2 describes the sample and data, Section 3 discusses the self-consistency of the method, Section 4 discusses the power of the t-tests used in the CSAD-based test, and Section 5 concludes the paper.

2. Sample and data

In this study, I selected the S&P 500 stock universe as of June 30, 2023, for the main sample pool. I retrieved daily gross returns, including distributions, of S&P 500 stocks from Bloomberg. The sample period spans from 2016 to 2022. I excluded any stocks that did not have consecutive daily returns from the full sample period, resulting in a pool of 454 stocks for the sample.

3. Self-consistency of the CSAD-based method

I followed the method proposed by Chang et al. (2000) to detect herding behavior in the stock market. I constructed CSAD for each day using Equation (1):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|r_{it} - \bar{r}_t|, \tag{1}$$

where N is the number of sample stocks, r_{it} is the return of stock i at time t, and $\bar{r}_t$ is the equally weighted average return of all sample stocks at time t.

$$CSAD_t = \alpha + \beta_1|\bar{r}_t| + \beta_2\bar{r}_t^2 + \varepsilon_t. \tag{2}$$

If herding behaviour exists in the market, β_2 should be negative and significant in the regression. The t value of the CSAD-based test for H_α: $\beta_2 < 0$ was the main variable of interest in this study. I also provided results on estimated H_α: β_2 when the t value was not appropriate to draw a conclusion.

3.1 Number of sample stocks and convergence of β_2

Whether sample pools of different sizes reach the same conclusion under identical market conditions is the first topic to address in this research. The method's power could be low if, despite including sufficient sample stocks, pools of different sizes yield divergent conclusions. Furthermore, researchers must consider the question of how many stocks are necessary for an acceptable sample size. If we can use 10 stocks to provide a solid conclusion on herding behaviour in the market, including 3,000 stocks in the sample would be pointless. I provided answers to the above questions based on simulations. The simulations to estimate the t values involve the following steps:

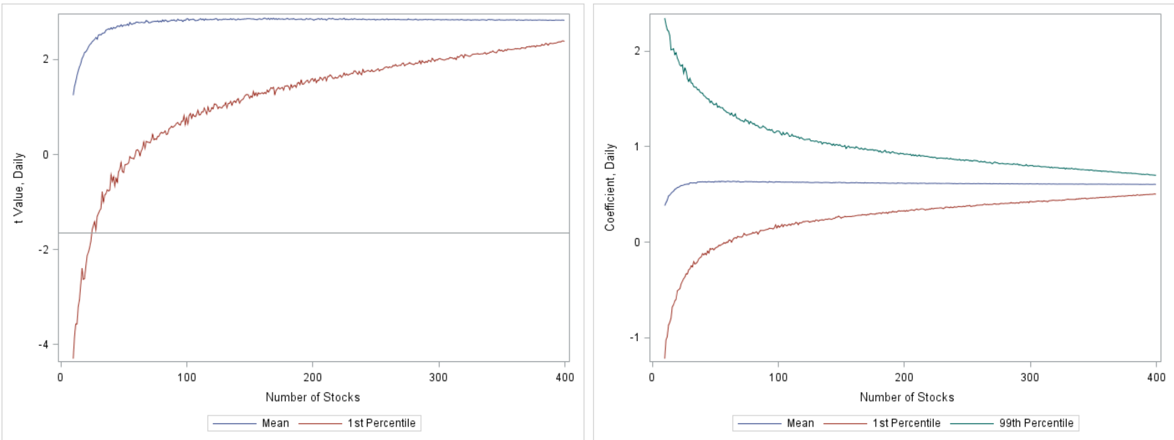
i. Sample N stocks from the sample pool. N is the number of sample stocks in this simulation.
ii. Obtain returns of the stocks in the sample period.
iii. Calculate CSADs and equally weighted "market" returns based on the sample stocks [Equation (1)].
iv. Estimate the t value based on Equation (2).
v. Repeat the process 5,000 times[1].

[1] The number of simulations is determined by separate tests. Please see details in Appendix

For each N, or each set of simulations, I estimated 5,000 t values and β_2s and used the results to draw conclusions on herding behaviour. N increases from 10 to 400[2]. Figure 1(a) shows the mean t value and 1st percentile of the t values estimated from the set of simulations for each N. The reference line at the bottom is the critical value of a 5% significance level given the number of observations, 1,821. As N increases, the mean t value stabilises to a level well above the critical value. The important indicator, 1st percentile of t values, is also consistently above the critical value after N moves beyond about 30. This means that as the number of sample S&P 500 stocks increases beyond about 30, at least 99% of simulations in a set have t values that indicate a failure to reject the null hypothesis (H0: $\beta_2 \geq 0$), consistently demonstrating that herding behaviour does not exist in this sample period in the US stock market. The results imply that we may not need 500 sample stocks to provide a solid conclusion on herding behaviour, although 10 or 20 stocks may also be insufficient. The exact necessary number of sample stocks may not be evident, but the findings suggest that more than 50 stocks could provide a consistent answer on herding behaviour in the stock market.

The conclusions were drawn based on one assumption: as the number of sample stocks increases, the estimated β_2 should converge to a stable level. If the estimated β_2 changes dramatically without a stable terminal level, this could indicate that the CSAD-based method is not reliable in detecting herding. However, Figure 1(b) shows that the mean β_2 converges, validating the assumption and demonstrating the self-consistency of the CSAD-based method.

Figure 1: Change in the Variables of Interest as the Number of Sample Stocks Increases



(a) (b)

3.2 Sample period length

Sample period length is another important factor. As shown in Table 1, the sample periods of previous studies vary. Sample period length determines the number of observations in the regression described by Equation (2), and affects test results and conclusions on herding. In this section, I

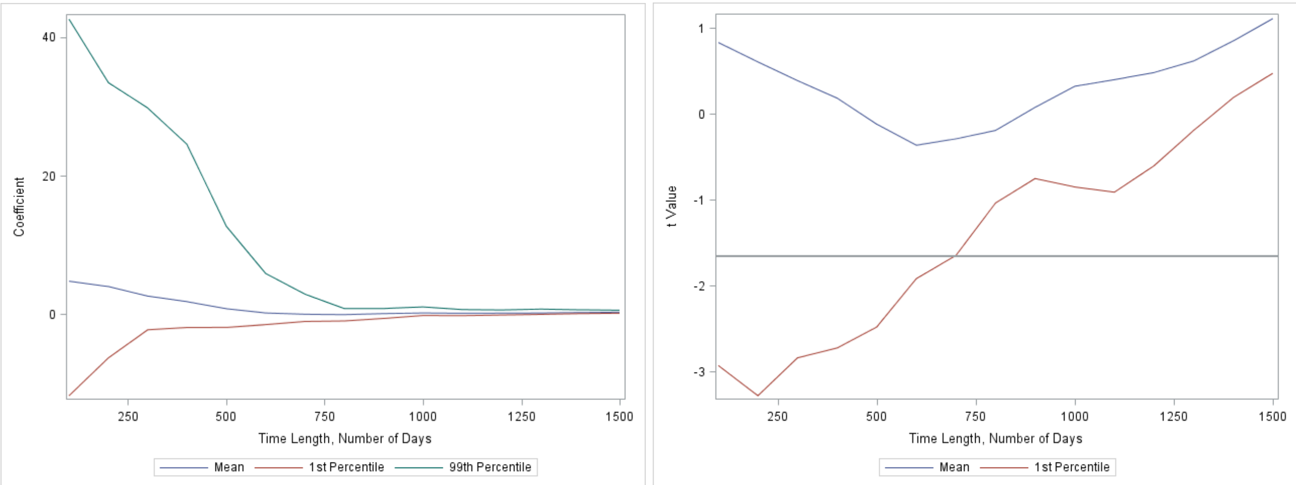
[2] *N* should not be close to the total number of stocks, 454, for this sample pool, or the simulations will provide almost identical *t* values.

provided evidence on the self-consistency of the method with respect to change in time length. I modified the first step of the procedure described in Section 3.1 as follows:

i. Sample *T* consecutive trading days from the whole period, 2016 to 2022, as the sample period of this simulation. All stocks are used as sample stocks. The start day of the sample period may not be the first trading day of 2016.

For each T, 5,000 t values and β_2s were estimated. T increases from 100 to 1,500. Figure 2 shows that the mean β_2 converges as the length of the sample period increases. After T reaches about 700, more than 99% of simulations have t values that indicate consistent no-herding conclusions. These results suggest that a sample period of at least 700 days can help researchers avoid inconsistent conclusions.

Figure 2: Change in the Variables of Interest as the Sample Period Length Increases



(a) (b)

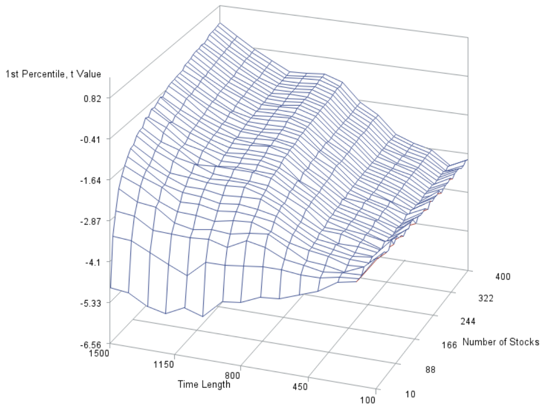
3.3 Number of sample stocks versus length of sample period

In the sample formatting process, stocks with missing values were excluded from the sample pool, creating a trade-off between the number of sample stocks and the length of the sample period. A longer sample period is likely associated with fewer stocks in the sample pool in many cases. This is especially an issue for stock markets without large trading volumes or solid trading records. If extending the sample period results in a lower number of sample stocks, one may question how the sample can be formed to maximise the consistency and power of the test. To study this topic, I modified the first step of the procedure described in Section 3.1 as follows:

i. Sample N stocks from the sample pool as sample stocks and T consecutive trading days from the whole period as the sample period in this simulation.

For each N and T, 5,000 t values were estimated. N ranged from 10 to 400 by 10, and T ranged from 100 to 1,500 by 100. As shown in Figure 3, the 1st percentile of t values increases as N and T increase. When the number of days and the number of sampled stocks are large, the 1st percentile of t values is well above the critical values, which are around 1.64. However, when the sample period is sufficiently long, the growth rate of the 1st percentile relative to the number of sample stocks is higher compared to its growth rate relative to the time length, provided the number of sample stocks is sufficiently large. The evidence indicates that when there is a conflict, it's more important to focus on increasing the number of stocks in the sample rather than extending the length of the sample period.

Figure 3: Change in 1st Percentile of t Values as the Sample Period Length and Number of Sample Stocks Increase



4. Power of the t-tests

The main results on herding are derived from the t-test for Hα: $\beta_2 < 0$. As a result, the power of the CSAD-based test should not be greater than the power of the t-test. A potential problem is that the power of t-tests in the regressions may be too low, making it unlikely to reject the false null hypothesis. Therefore, there is a significant probability that herding exists, but the model may not be capable of detecting it. The homogenous no-herding conclusions in the simulations may not be the results of no-herding conditions in the market; instead, they may be driven by the weak power of the t-tests. To address this issue, I followed the method described by Cohen (1988) and used Equations (3) to (5) to estimate the power of the t-tests in the regressions.

$$Cohen's\ f^2 = \frac{R^2_{with\ \bar{r}_t^2} - R^2_{without\ \bar{r}_t^2}}{1 - R^2_{with\ \bar{r}_t^2}}, \tag{3}$$

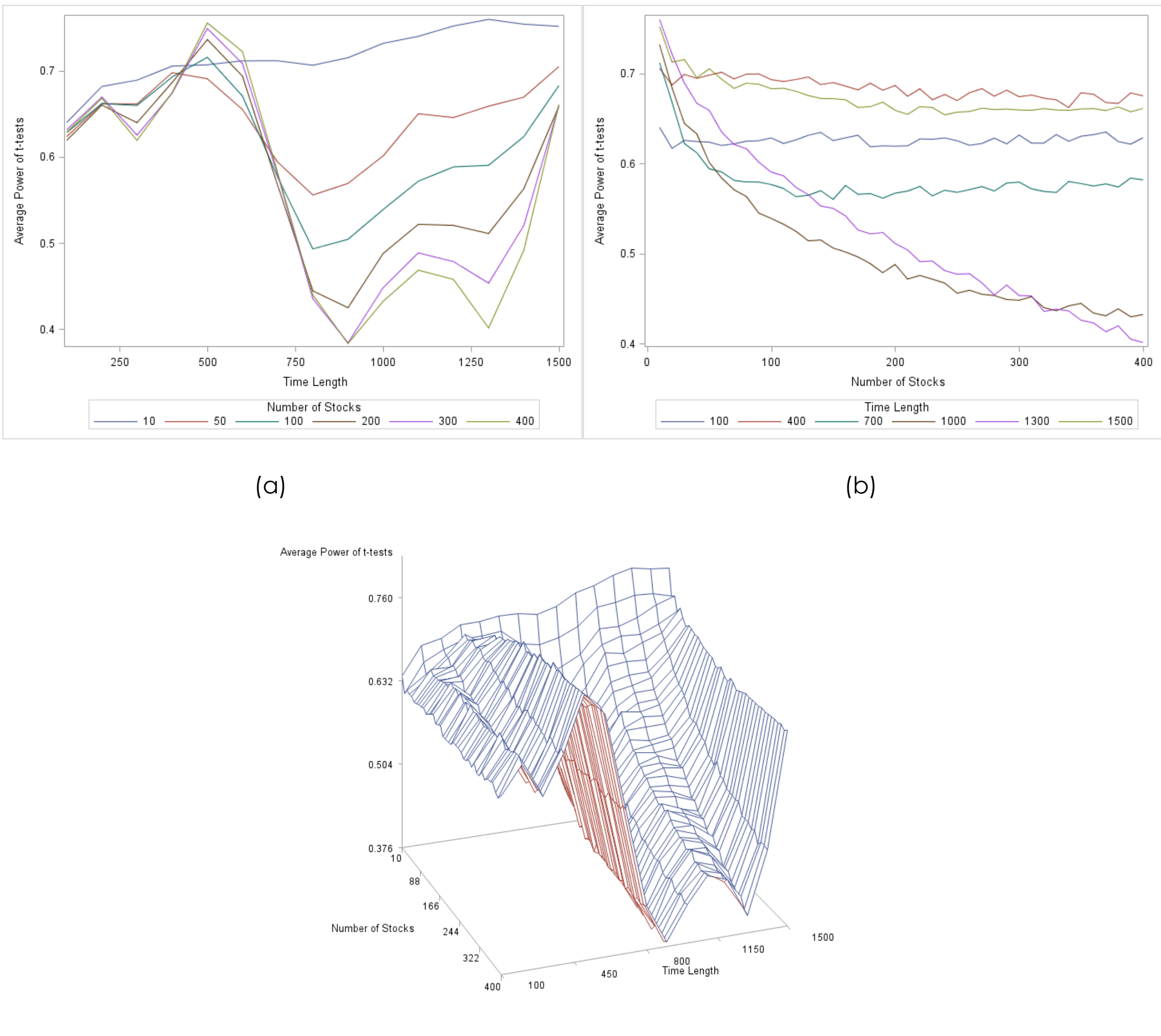
$$\lambda = Cohen's\ f^2 T, \tag{4}$$

$$Power = F(\lambda, u, v), \tag{5}$$

where $R^2_{with\ \bar{r}_t^2}$ and $R^2_{without\ \bar{r}_t^2}$ are the R^2s of the full model [Equation (2)] and the model without $\bar{r}_t^2$, respectively. T is the number of observations in regressions. $F(\lambda, u, v)$ is the cumulative probability given F-value, λ, and degrees of freedoms, u, v. Because there is only one variable of interest, $\bar{r}_t^2$, u is set to 1. Lastly, v is T- u -1. I used the procedure in Section 3.3 but focused on the power of t-tests instead of the t value. The number of observations, which determines the degree of freedom for the t-test, is a result of the sample period length and observation frequency in this section. The number of sample stocks does not directly impact the number of observations because the regression described by Equation (2) is a pure time-series regression.

The average power of each set of simulations for different N and T was reported in Figure 4. As a rule of thumb, it is believed that 80% is an acceptable level of testing power (see, for example, De Winter, 2019; Serdar et al., 2021). The average power ranges from 37.62% to 75.98% with a mean of 59.37%, indicating low testing power in this study. Surprisingly, the number of observations in regressions does not play a larger role in the testing power. As shown in Figure 4(a), the testing power first decreases significantly and then increases as the number of days increases. The pattern observed with fewer sample stocks exhibits a flatter curve. In theory, a higher number of observations, namely, days in this study, should be associated with higher testing power. However, the evidence does not support this expectation, indicating potential problems with the model specifications. Furthermore, Figure 4(b) indicates that as the number of sample stocks increases, the testing power decreases. Additionally, longer sample length is associated with a steeper dive in average power as the number of sample stocks increases. As discussed in Section 3.1, a higher number of sample stocks should make the testing results more stable. However, the findings in this section are not consistent with this expectation. The declining testing power raises another concern: when sample sizes are large, it may be that the consistent conclusions about herding are driven by the low testing power, which questions the model's ability to accurately detect herding. The joint effect shown in Figure 4(c) confirms the findings.

Figure 4: Change in Average Power of T-tests as the Sample Period Length and Number of Sample Stocks Increase



(a) (b)

(c)

Two factors may contribute to the low power of the t-tests. First, stock returns are featured in a high level of noise and are influenced by many market and fundamental factors. The dependent variable, CSAD, is itself a deviation measure, which could be noisy. Second, the model includes only two independent variables, which may not be sufficient to explain the whole variance of the dependent variable. As a result, R^2s of the full and reduced models are low. The average R^2 is about 35.89% in this section, and some previous studies document even lower R^2 (see, for example, Espinosa-Méndez and Arias, 2021; Ukpong et al., 2021). The low R^2 leads to a relatively low $Cohen's\ f^2$ and low power of a t-test. Future research in this field should take the power of the herding test into consideration, especially when R^2 of the model is low.

5. Conclusion

The CSAD-based method provides a convenient way for researchers to detect herding behaviour in a market. Therefore, it is important to know about the power and features of the method. In this study, I find that the CSAD-based method provides consistent results if the number of stocks included in the tests is more than 30 and/or the sample period is more than 700 trading days. Moreover, evidence shows that as additional stocks and trading days are included in the tests, the method tends to produce more consistent conclusions on herding behaviour. These findings support the CSAD-based method; however, evidence also demonstrates that the power of the t-tests used in the method is low overall, indicating that the method may suffer from low testing power problems. Researchers should take the testing power into consideration when conducting herding tests based on CSAD.

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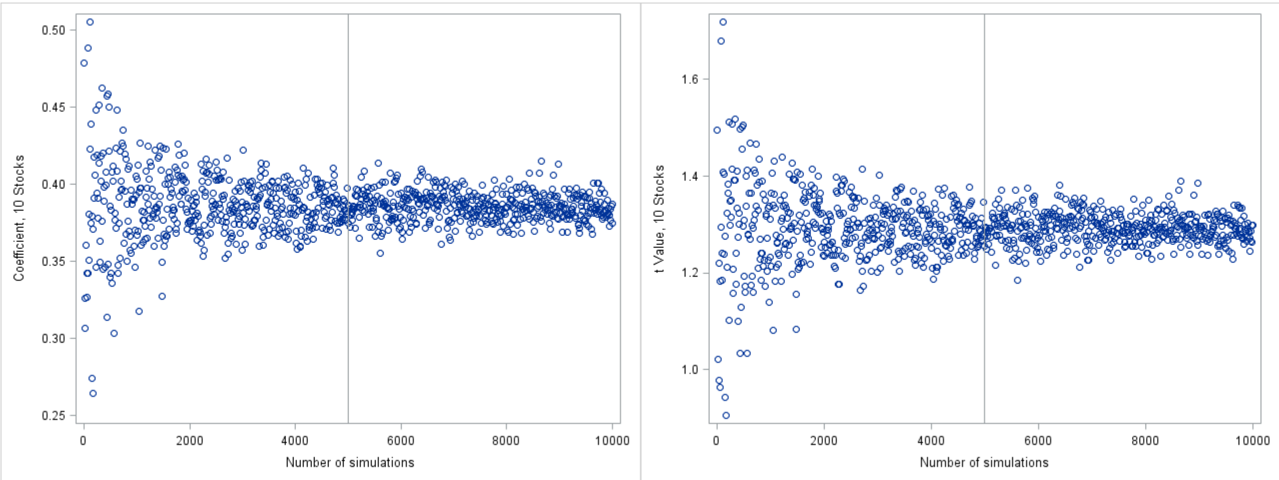
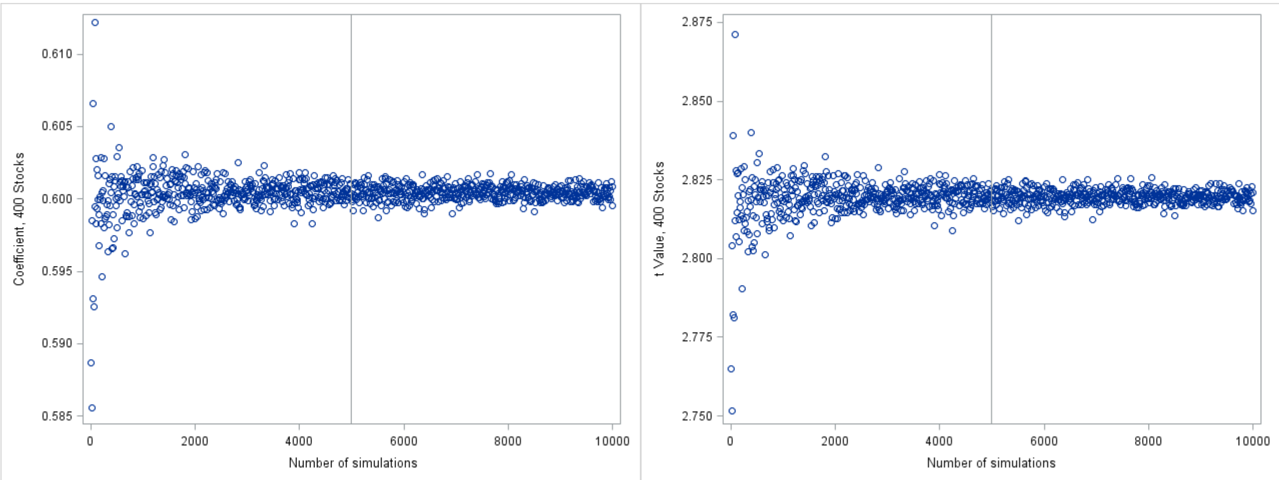
Appendix A: Choosing the number of simulations in each simulation set

To find a reasonable number of simulations per set for the main results, I ran sets of simulations to check when the variables of interest were stabilised. The procedure is similar to the one described in Section 3.1. The numbers of sample stocks from the sample pool were fixed at 10 and 400. The number of simulations in each set increased from 10 to 10,000 by 10. Figure A.1 shows the results. After the number of simulations in each set reached 5,000, the mean β_2 and the mean t value converged to stable levels. The number of sample stocks in the sampling process is relevant, but the results were consistent. In this study, I have selected 5,000 simulations for each set (as indicated in Figure A.1) to guarantee comprehensive and reliable results.

Figure A.1: Change in Variables of Interest as the Number of Simulations Increase



(a) (b)



(c) (d)

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EVALUATING STOCK SELECTION IN THE SAAS INDUSTRY: THE EFFECTIVENESS OF THE RULE OF 40

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Abstract

The Rule of 40 is a popular financial guideline used by software-as-a-service (SaaS) industry participants to assess the operational health of the companies. This paper investigates the effectiveness of the Rule of 40 as a stock selection criterion. Our study analyses a sample of 1771 SaaS companies worldwide spanning the period 2003-2022. The findings demonstrate that the Rule of 40 adds value and delivers a moderately high Sharpe ratio as a stock selection tool. A modified rule, the SaaS Investing Rule of 65, is proposed and found to outperform the Rule of 40 in identifying relative winners and losers within the SaaS space. The effectiveness of the rules raises practical implications for investors and analysts. Additionally, we explore the effectiveness of alternative versions of the Rule of 40 using different measures of profitability, as well investigate whether the returns are driven by traditional style factors.

Keywords: Rule of 40, SaaS, software-as-a-service, stock selection, SaaS Investing Rule of 65

1. Introduction

The software-as-a-service (SaaS) industry is characterised by rapid innovation, intense competition, and evolving business models. Because the industry is predominantly governed by the network effect, where each new customer increases the value of the product for all existing for future customers, young SaaS companies frequently prioritise growth over short-term profitability to expand their market share. However, as these businesses approach the top of their initial S-curves, revenue growth slows, and profitability becomes a greater focus. Due to the lag between bookings and revenues, companies facing upfront costs for customer acquisition and R&D must make strategic decisions on how to balance growth and profitability, and this is where the Rule of 40 comes in.

The Rule of 40 was introduced by Brad Feld (2015). It is essentially a financial guideline that provides a holistic framework for evaluating SaaS companies and it states that for a healthy SaaS company, the sum of its revenue growth rate and profitability margin should be higher than 40%. By taking into account these two key factors, the rule provides a comfortable trade-off between growth and profitability. A combined value of 40% or higher therefore indicates that a company is striking a healthy balance between the two, while a value below 40% suggests potential issues in either area.

Despite its simplicity, beating the Rule of 40 appears to be a lot more challenging. Roche and Tandon (2021) examined more than 200 software companies of various firm sizes between 2011 and 2020 and found that only one-third of them were able to achieve the Rule of 40, with even fewer able to sustain it. Similarly, Depeyrot and Heap (2018) researched the performances of 124 publicly traded software companies to identify those that outperformed the Rule of 40 over three and five years. They found that only 40% of them were able to exceed the rule in the single year of 2017, and only 25% and 16% were able to outperform the rule for three or more years and for all five years respectively, adjusted for mergers and acquisitions.

As expected, the rule has become a favourite rule of thumb for venture capitalists and SaaS industry watchers, including boards and management teams, to assess their company's operating performance. For investors and analysts seeking attractive investment opportunities within the dynamic SaaS sector, the rule may also help identify promising companies. However, despite its potential as a useful stock selection tool, little research has been conducted on its efficacy as one.

This paper seeks to study the effectiveness of the Rule of 40 as a stock selection criterion in the SaaS industry. The study examines 1771 SaaS firms across the world between 2003 and 2022, categorising them into long or short portfolios based on their ability to satisfy the Rule of 40. The study finds that the median SaaS company, whether it satisfies the Rule of 40 or not, generally delivers negative returns over the sample time period. However, the median stock within the long portfolio significantly outperforms the median stock in the short portfolio over time, leading to fairly consistent outperformance of a long-minus-short strategy within the SaaS stock universe. These findings remain even when country effects are taken into consideration. The study also finds that EBITDA margin is the most effective measure of firm profitability compared to EBIT margin and net margin. The study further proposes a modified SaaS Investing Rule of 65 that combines the Rule of 40 with valuation consideration. The proposed rule outperforms the Rule of 40 in identifying relative winners and losers. An analysis of the macroeconomic sensitivities of both the rules evinced that the Rule of 40 exhibited a superior performance in contracting growth and subdued inflation environments relative to its performance in expanding growth and escalating inflation environments. Conversely, the SaaS Investing Rule of 65 demonstrated a more favourable outcome in expanding growth and escalating inflation periods compared to its performance in contracting growth and subdued inflation periods. Furthermore, stress testing conducted across major market crises indicated that both investment rules generally yielded positive returns, with the SaaS Investing Rule of 65 outperforming the Rule of 40, except during the Taper Tantrum and the Covid-19 pandemic episodes.

By investigating the Rule of 40, the study contributes to the existing literature on financial metrics for stock selection and provides insights into its usefulness for investors and analysts. The study aims to enhance understanding the Rule of 40 and its implications for decision-making in the software and technology industry. Additionally, the study proposes a modified rule for investing in SaaS stocks that takes into account both the Rule of 40 and stock valuations, which may be useful to practitioners seeking to identify attractive investment opportunities in the SaaS industry. Overall, the study provides valuable insights into the effectiveness of the Rule of 40 as a stock selection criterion in the SaaS industry and highlights the importance of considering both growth and profitability when evaluating SaaS companies.

This paper is structured as follows: Section 2 provides a brief literature review and the economic rationales underpinning the Rule of 40. Section 3 gives an overview of the data used in the study and the methodology employed. Section 4 reports our empirical findings and Section 5 concludes the paper.

2. Literature Review

2.1 Background

The software industry has undergone a substantial transformation in recent years, marked by a pronounced shift towards the SaaS model. This development, influenced by the widespread adoption of cloud computing and the allure of flexible, scalable software solutions, has led to an increasing demand for effective valuation methodologies that accurately reflect the economic realities of SaaS companies. Although SaaS represents a segment within the broader software industry, it exhibits unique characteristics that challenge the application of valuation methods conventionally used for traditional software companies.

In particular, SaaS businesses face substantial challenges in achieving profitability during their start-up and early growth phases, compared to traditional software businesses. These challenges primarily stem from three fundamental differences between SaaS and traditional software business models.

The first distinguishing factor between traditional software and SaaS companies is the timing of revenue and cost recognition. Both types of companies incur immediate product development costs and customer acquisition costs (CAC) to generate sales. However, the timing of revenue recognition varies significantly between the two. Traditional software firms, such as Oracle and SAP, typically generate revenue through the one-off sale and delivery of perpetual licenses and subsequent upgrades (Osterwalder & Pigneur, 2010), recognising these revenues upfront. This aligns the timing of revenue and expenses, enabling these firms to achieve profitability early in their lifecycle. In contrast, SaaS firms operate on a subscription-based model, with customers subscribing to the software for a period of time, typically monthly or annually (Dempsey & Kelliher, 2017). Accounting rules dictate that these revenues are recognised over the time that the service is delivered (Guo & Ma, 2018), resulting in a delay in revenue recognition compared to traditional software firms. This leads to a misalignment between revenue and expenses. Consequently, SaaS businesses often experience initial losses, as a single subscription fee does not cover the associated customer acquisition cost. As SaaS firms acquire more customers, they incur additional costs, while the return on investment is only realised over the subscription period (Gardner, 2015). These losses can intensify with increased customer acquisition. Furthermore, the timing of cash flow is also misaligned, as customers typically pay for the service periodically, while the company must cover its expenses immediately. This results in a scenario where growth initially exacerbates cash flow, as the faster a SaaS company grows, the more upfront sales expense it incurs without the corresponding incoming cash from customer subscriptions.

The second distinction between Software as a Service (SaaS) enterprises and traditional software firms is manifested in their respective expense trajectories. Two crucial factors to examine in this context are the cost of service delivery and the financial implications of customer churn. In the realm of traditional software companies, upon purchase, the customer effectively takes over ownership of the software and manages it using their own IT infrastructure. This arrangement encompasses assuming the responsibilities for installation, updates, licensing, maintenance, and other ancillary costs associated with the software's operation. Consequently, traditional software companies experience minimal financial impact from customers ceasing to use their software, as the initial purchase typically suffices to recoup the customer acquisition costs (CAC) (Bandulet, 2017).

In contrast, SaaS models centralise the software and hardware within the vendor's infrastructure, assigning the onus of maintenance, updates, and upgrades predominantly to the vendor. This structural difference renders SaaS businesses particularly vulnerable to the effects of churn (York, 2012). The financial ramifications of churn are especially acute if a subscription is terminated before the CAC has been fully recuperated (Bandulet, 2017). As a result, SaaS entities must prioritise not only the attraction of new customers but also the retention of existing ones to optimise the lifetime value derived from each customer relationship. This dual focus on acquisition and retention engenders a steeper expense curve for SaaS companies in comparison to their traditional software counterparts.

The third distinction between SaaS businesses and traditional software companies is manifested in the predictability and profitability of their long-term revenue streams. SaaS models, predicated on subscription-based revenue, offer a more stable financial outlook once a robust subscriber base has been established. This stability stems from the inherent "stickiness" of SaaS offerings, whereby customers, having outsourced their software management to a third-party vendor, are more likely to maintain their subscription over an extended period. This enduring customer relationship is further reinforced by the challenges associated with switching SaaS providers. The deeply integrated nature of SaaS solutions within business processes, coupled with the complexities of budget decentralisation and department-specific utilisation, significantly heightens the barriers to switching providers, thereby fostering a predictable and continuous revenue flow for the SaaS provider.

Contrastingly, traditional software models, which predominantly rely on single-purchase transactions, do not facilitate the establishment of long-term customer relationships to the same extent, nor do they benefit from recurrent revenue streams. Moreover, SaaS enterprises exhibit enhanced profitability. SaaS platforms are engineered for seamless scalability in response to the evolving requirements of customers. Leveraging cloud-based infrastructure, SaaS vendors can adeptly accommodate surges in demand without necessitating substantial investments in infrastructure. This scalability not only enables SaaS companies to cater to an expanding clientele with minimal additional costs but also amplifies profitability.

The scalability characteristic is further propelled by the pronounced network effects inherent in SaaS business models, which, as Shim and Lee (2012) elucidate, augment the product's value and contribute to the exponential valuation growth of companies like Zoom with each new active user. Additionally, SaaS providers can capitalise on economies of scale by servicing multiple clients on a communal infrastructure, thereby distributing the costs associated with development, maintenance, and support over a broader customer base. This distribution mechanism effectively reduces per-unit costs and, as the customer base burgeons, significantly elevates profit margins.

Given these unique characteristics, SaaS entities often adopt aggressive sales and marketing strategies during periods of heightened adoption to capitalise on early growth opportunities. This approach is deemed essential within the highly competitive, winner-take-all markets characteristic of the SaaS industry (Bandulet, 2017). The establishment of a robust subscription base subsequently facilitates the transition to more predictable and profitable revenue streams for SaaS companies.

The distinct operational and financial dynamics of SaaS companies have prompted a scholarly consensus advocating for differentiated management and valuation practices for these entities in contrast to traditional software firms (Li et al., 2017; Cadambi & Easwaran, 2016; Li et al., 2017; Skok, 2017). A salient challenge identified in this discourse pertains to the strategic dilemma SaaS managers face in balancing the prioritisation of short-term growth against the pursuit of long-term profitability. This conundrum is exacerbated by the temporal disparities in revenue and expense recognition, as well as the strategic imperative to build an economic moat upon achieving critical mass. Despite the apparent dichotomy between growth and profitability in the nascent stages of a SaaS company's development, Dolgaia and Sorokina (2020) find that most industry experts agree that they remain the most important metrics to focus on for SaaS companies.

Recent scholarly investigations have similarly underscored the pivotal roles of growth and profitability in the valuation of Software as a Service (SaaS) firms. Research conducted by Gardner (2016) and Kellogg (2013) elucidates that SaaS entities demonstrating superior revenue growth rates relative to their similarly-sized counterparts command higher market valuations. This assertion is further corroborated by Newton and Schlecht (2016), who, upon analysing 63 publicly listed SaaS corporations over the 44 quarters since 2005, identified a positive correlation between both revenue growth and EBITDA margin with corporate valuations. Notably, during the examined period, revenue growth was ascertained to be of twofold importance compared to EBITDA margin, although the significance attributed to profitability has experienced an uptick between 2014 and 2015. This trend towards an increased valuation of profitability was affirmed by Heimann and Rathi (2017), who observed a market inclination towards rewarding profitable SaaS companies.

2.2 Theoretical Framework

The 'Rule of 40' has emerged as a critical evaluative framework within the technology sector and venture capital milieu for appraising the balance between growth and profitability of SaaS firms. Popularised by Techstars' Brad Feld (2015) on his popular blog Feld Thoughts, this heuristic posits that the aggregate of a software company's revenue growth rate and profitability margin should surpass 40% to denote a healthy operational state (Feld, 2015). The utility of the 'Rule of 40' is twofold: it furnishes investors with a comprehensive metric to assess the health of a company (Depeyrot & Heap, 2018; Kellogg, 2013; Kellogg, 2023; Cummings, 2015; Strazzulla, 2016), and it incentivises SaaS providers to concurrently prioritise profitability and growth, thereby aiding in the establishment of strategic objectives (Depeyrot & Heap, 2018).

Eriksen (2022) posits that the 'Rule of 40' constitutes the paramount Key Performance Indicator (KPI) for maximising a SaaS company's valuation. This assertion is supported by Löfgren and Petterson (2021), who, in their study on performance measures and quality criteria for SaaS B2B companies, found that two out of seven companies identified the 'Rule of 40' as among the top five of their most important measurements. Latka (2022) further suggests that this rule can serve as a guideline for companies, particularly those achieving $1 million in recurring revenues, to balance their capacity for investment without compromising earnings. Complementing this, Depeyrot and Heap (2018) observed that companies surpassing the 40% threshold typically enjoy valuations twice as large as those failing to meet this criterion. Collectively, these studies highlight the 'Rule of 40' as an indispensable benchmark for SaaS companies, guiding them towards a balanced pursuit of growth and profitability to maximise their market valuation.

3. Data and Methodology

The methodology employed in this study aims to evaluate the effectiveness of the Rule of 40 as a stock selection criterion in the SaaS industry. The following sections outline the data collection process, sample selection, and calculation of the Rule of 40. All calculations within the study are executed using the R software.

3.1 Data

All the data for this study were downloaded from FactSet. Key financial indicators including revenue growth rate, profit margin, and stock returns were collected monthly over the twenty-year period of January 2003 to December 2022. Detailed explanations of the variables and their respective Factset mnemonics are provided in Table 1. In our analysis, we include only those firm-year datapoints that have the necessary data for calculating the Rule of 40 and the corresponding price returns.

Table 1: Definitions of variables

Variable	Factset mnemonic	Definition
Monthly stock returns	P_PRICE_RETURNS	Monthly total returns of the security in USD.
Monthly country-neutral stock returns	MSCI_TOTAL_RET_IDX	Monthly total returns of the security in USD minus Monthly total returns of the MSCI country index in USD.
One-year sales growth	FF_SALES_GR	Calculated as the year-over-year percent change in Net Sales or Revenue (FF_SALES).
EBITDA margin	FF_EBITDA_OPER_MGN	Calculated as EBITDA (Operating Income Plus Depreciation & Amortization) (FF_EBITDA_OPER) divided by Net Sales (FF_SALES).
EBIT margin	FF_EBIT_OPER_MGN	Calculated as EBIT - Operating Income (WSF_EBIT_OPER) divided by Net Sales (WSF_SALES).
Net margin	FF_NET_MGN	Calculated as Net Income (FF_NET_INC) divided by Net Sales or Revenue (FF_SALES), multiplied by 100
Price to sales	FF_PSALES	Calculated as Price - Close (FF_PRICE_CLOSE_FP) divided by Sales Per Share (FF_SALES_PS).

3.2 Sample Selection

We identify software-as-a-service companies globally using Revere Business Industry Classification System (RBICS), a comprehensive, bottom-up structured taxonomy that classifies companies according to the products and services they provide. Companies with RBICS that correspond to "software" are screened, which yields us the final sample which comprises a diverse set of 1771 SaaS companies operating a range of software, including Retail Industry Software, Mobile Platform Applications Software and Compliance ERP Software, within various economic sectors such as Finance, Technology and Industrials. Due to occurrences of delisting and bankruptcies among certain SaaS companies within the sample period, as well as some companies being listed midway through the period, the resultant sample is characterised by an unbalanced panel structure.

Figures 1 and 2 show the breakdown of our sample set by country and sector respectively over time. We can see that while there were only about 300 SaaS companies in 2023, that number steadily increased by almost six-fold over the next two decades, with US, Japan and China accounting for approximately two-fifths of them. In terms of economic sectors, Technology is expectedly where most of the SaaS companies are found, followed by Finance.

Figure 1: Breakdown of global SaaS universe by country

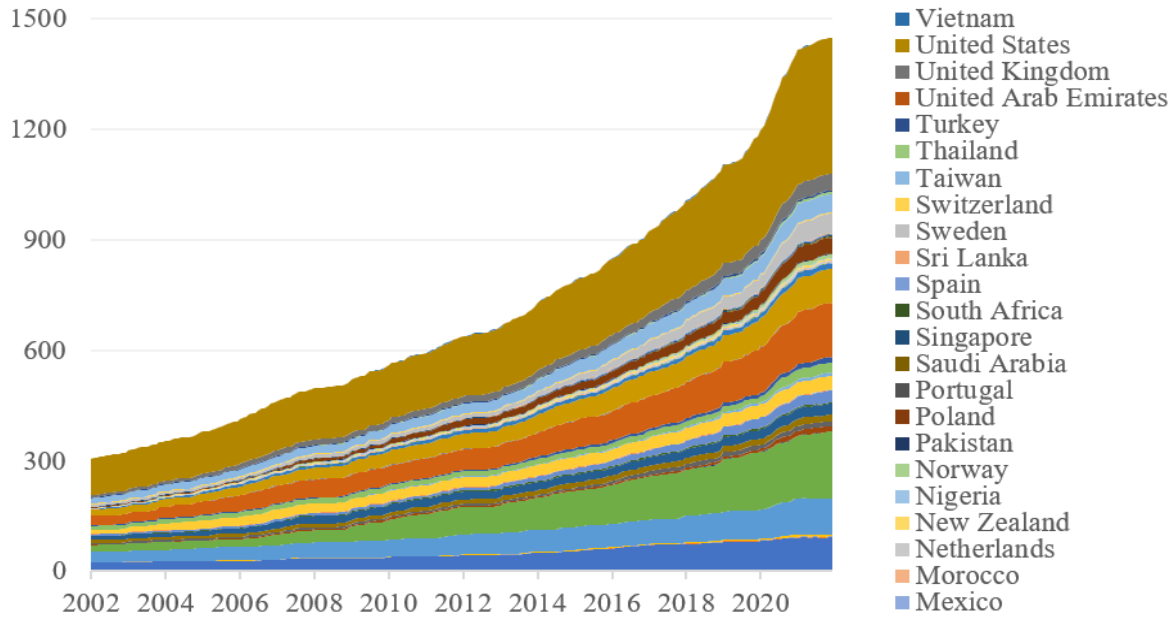
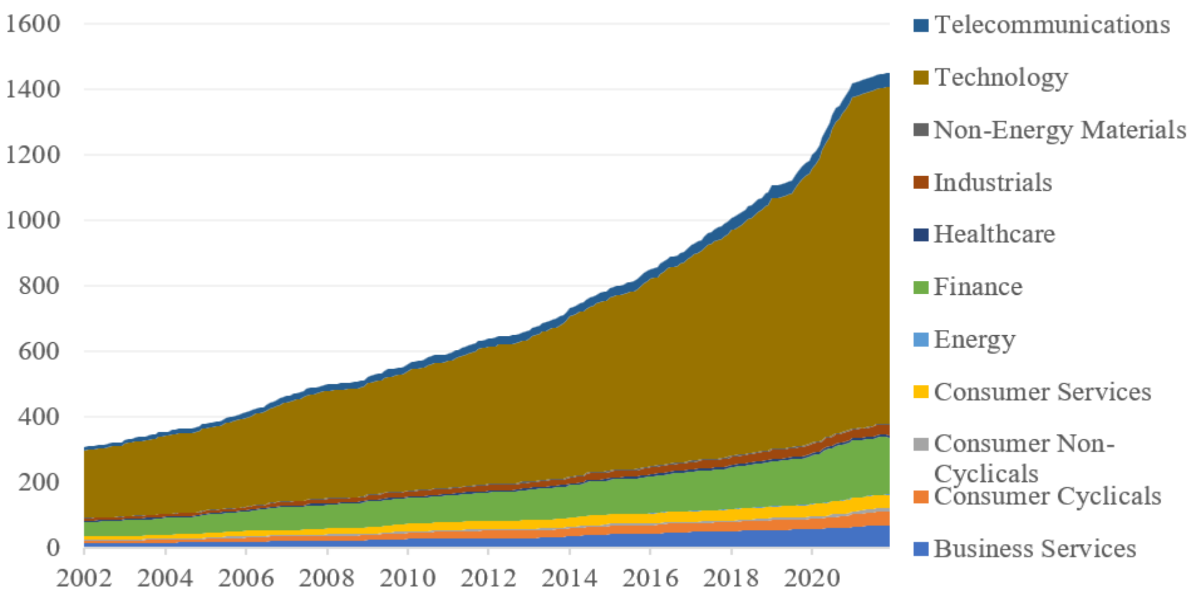


Figure 2: Breakdown of SaaS universe by industry sector



3.3 Calculation of the Rule of 40 and Portfolio Formation

The Rule of 40 (R40) is calculated by summing the company's revenue growth rate and profit margin. We represent revenue growth rate as the percentage change in sales over the last year. For the definition of profitability, there is no generally agreed upon measure. The margins of Unlevered Free Cash Flow, Operating Income, and Earnings Before Interest, Tax, Depreciation and Amortisation

(EBITDA) are all different measures of profitability that Feld (2015) consider to be legitimate candidates for use in the Rule of 40 calculation. Following Feld (2015) and common practice, we use EBITDA margin, defined as EBITDA divided by sales, as our measure of profitability.

The formula for calculating the Rule of 40 is therefore as follows:

$$\text{Rule of } 40 = \text{Sales growth over last year} + \text{EBITDA margin} \tag{1}$$

The combined value is then compared to the threshold of 40% to determine whether the company meets the Rule of 40 criteria. The companies that met or exceeded the Rule of 40 threshold are categorised into the long portfolio while the ones that fail the rule are put into the short portfolio, with the stocks in the respective portfolios being equally weighted, The monthly median returns of the portfolios are then calculated. Due to the existence of extreme outliers in the returns of our sample set, we use median, as opposed to mean, to represent the average returns of the portfolios. We also calculate the returns of a long-minus-short portfolio to capture the excess returns generated when using the Rule of 40 as a stock selection criteria.

4. Empirical findings

4.1 Descriptive statistics

Table 2 provides the descriptive statistics of the variables utilised in this study, including monthly stock returns, monthly country-neutral stock returns, one-year sales growth, EBITDA margin, EBIT margin, net margin, and the Rule of 40. The monthly returns and sales growth variables exhibit positive skewness to the right, while the margin variables are all negatively skewed to the left. The sample universe displays high kurtosis across all variables, indicating that the data is skewed to the right and heavily tailed with outliers. The positive mean return of the average SaaS firm and the negative median return suggests that the data is significantly impacted by extreme outliers, supporting the use of the median to represent the average returns of the formed portfolios. The mean of the Rule of 40 variable indicates that, on average over time, only 30% of companies satisfy the Rule of 40, consistent with the findings of Roche and Tandon (2021) and Depeyrot and Heap (2018).

Table 2: Descriptive statistics

	Monthly stock returns	Monthly country-neutral stock returns	One-year sales growth	EBITDA margin	EBIT margin	Net margin	Rule of 40
Mean	38.405	37.895	416.477	-5913.99	-6011.84	-7824.89	0.301
Median	-0.513	-1.602	9.878	8.368	3.379	2.379	0.000
Standard deviation	9721.13	9735.117	19740.09	440841.5	448082	637481.3	0.459
Skewness	389.801	389.241	105.239	-125.125	-125.535	-127.451	0.87
Kurtosis	160875.618	160413.775	12244.035	15955.11	16052.23	16418.73	1.756

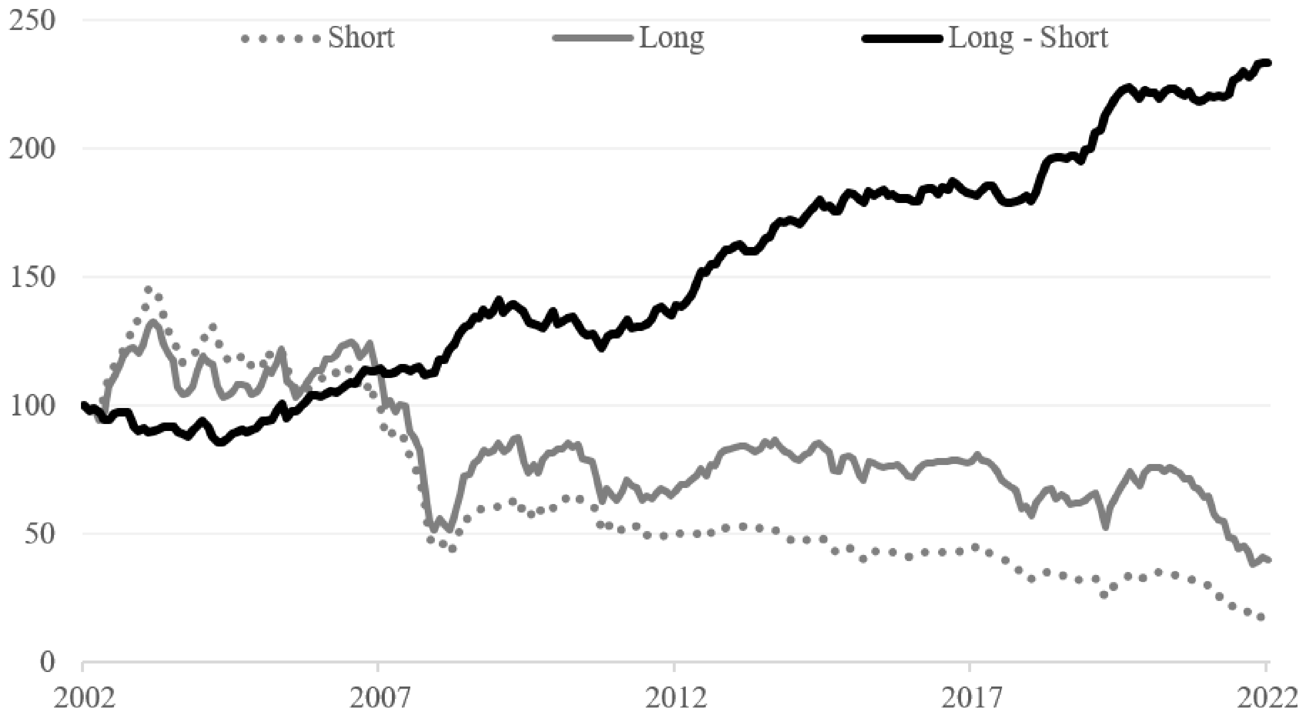
4.2 Rule of 40

The findings of the backtesting analysis are presented in Panel A of Table 3. Despite the commonly held belief that the SaaS industry is a high-growth and high-return sector, the median stock return of SaaS companies, regardless of their adherence to the Rule of 40 criteria, is predominantly negative. The median stock in the long portfolio generated positive monthly returns only 50% of the time, while the median stock in the short portfolio achieved the same around 40% of the time. Nonetheless, as a stock selection criterion to differentiate the winners from the losers within the SaaS industry, the Rule of 40 has proven to be effective, delivering positive annualised returns, a moderately high Sharpe ratio, and a high win ratio (defined as the proportion of positive-returns months). The efficacy of the Rule of 40 has remained consistent over time, with the cumulative returns of the long-minus-short portfolio increasing over time, as illustrated in Figure 3.

Table 3: Portfolio tests (January 2003 - December 2022)

		Rule of 40	
		Pass	Fail
	Long - Short	Long	Short
Panel A: Absolute returns			
Return (ann)	4.403	-3.120	-7.523
Risk (ann)	5.510	16.860	15.114
Sharpe ratio	0.799	-0.185	-0.498
Win ratio	61.3%	50.0%	42.9%
Panel B: Country-neutral returns			
Return (ann)	4.435	-11.911	-16.346
Risk (ann)	5.832	7.681	6.642
Sharpe ratio	0.760	-1.551	-2.461
Win ratio	60.4%	30.0%	15.4%
Panel C: Using EBIT margin			
Return (ann)	1.611	-5.096	-6.707
Risk (ann)	6.195	17.249	15.094
Sharpe ratio	0.260	-0.295	-0.444
Win ratio	51.7%	48.3%	44.6%
Panel D: Using Net margin			
Return (ann)	0.592	-5.827	-6.419
Risk (ann)	6.814	17.755	15.034
Sharpe ratio	0.087	-0.328	-0.427
Win ratio	52.9%	47.9%	46.3%
Panel E: SaaS Investing Rule of 65			
Return (ann)	10.562	-1.947	-12.509
Risk (ann)	5.749	15.312	16.112
Sharpe ratio	1.837	-0.127	-0.776
Win ratio	74.6%	50.0%	39.2%

Figure 3: Time series plots of the cumulative returns of long, short and long-minus-short portfolios formed on the Rule of 40 (January 2003 – December 2022)



Note: This chart shows the cumulative monthly returns of the long, short and long-minus-short portfolios formed on the Rule of 40 (Rule of 40). The long portfolio consists of companies which satisfy the rule while the short portfolio consists of companies that fail the rule. Monthly median returns from January 2003 to December 2022 are used for the calculations.

4.3 Country-neutral returns

In order to eliminate the influence of country-specific factors, we also assess the country-neutral returns of the three portfolios by computing the returns of the stocks relative to their respective MSCI country indices. Panel B of Table 2 presents the country-neutral returns of both the long and short portfolios, which are even more disappointing than the earlier results, with both portfolios delivering double-digit negative relative returns. However, the results of the long-minus-short portfolio remain relatively unchanged, which confirms the effectiveness of the Rule of 40 as a stock selection criterion within the SaaS industry.

4.4 Alternative measures of profitability

While EBITDA margin is the preferred profitability metric in the calculation of the Rule of 40, alternative measures such as EBIT margin and net income margin can also be used. In Panels C and D of Table 2, we evaluate the performance of the long-minus-short portfolios using these alternative metrics. Both alternative measures exhibit poor performance compared to EBITDA margin, delivering low positive annualised median returns and negligible Sharpe ratios over the sample period.

4.5 Fama-French factors

To investigate whether the efficacy of the Rule of 40 is simply a result of style factors within the market, we perform a regression analysis of the relationship between the monthly excess returns of the long-minus-short portfolio formed on the Rule of 40 and several factors, including the market premium (Mkt-RF) and the Fama-French equity anomaly factors of size (SMB), value (HML), profitability (RMW), and investment (CMA). The monthly returns of these factors are obtained from the website of Kenneth French[1].

Table 4 provides the results of the analysis. The intercept of the regression is 0.373, which represents the expected excess returns of the long-minus-short portfolio when all of the independent variables are equal to zero. The intercept is statistically significant at the 1% level, indicating that the long-minus-short portfolio generates positive excess returns that are not explained by the market premium or the Fama-French factors. The regression coefficient for Mkt-RF is 0.069, which is also statistically significant at the 1% level. This suggests that the excess returns of the long-minus-short portfolio are positively related to the market premium.

Table 4: Long-minus-short portfolio alpha and beta with respect to market and Fama-French factors (January 2003 - December 2022)

	Intercept	**Mkt-RF**	**SMB**	**HML**	**RMW**	**CMA**
Regression coefficient	0.373**	0.069**	-0.126	-0.020	-0.092	-0.160
	(3.494)	(2.705)	(-1.832)	(-0.301)	(-0.984)	(-1.686)
Adjusted R-squared:	0.074			No of observations:		240

Note: This table reports the regression results of the monthly excess returns of the long-minus-short portfolio formed on the Rule of 40 versus the market premium and the Fama-French equity anomaly factors SMB, HML, RMW and CMA. t-statistics are shown in the parentheses. Significance levels: ** = 1%, * = 5%.

However, the regression coefficients for SMB, HML, RMW, and CMA are all not statistically significant at the 5% level, which indicates that the returns from the Rule of 40 are not significantly impacted by the Fama-French factors. In fact, the low adjusted R-squared of the regression of 0.074 suggests that other factors besides the market premium and Fama-French factors may be driving the excess returns of the long-minus-short portfolio.

Overall, the regression analysis indicates that the efficacy of the Rule of 40 is not simply a result of style factors within the market, as the excess returns of the long-minus-short portfolio are not significantly impacted by the Fama-French factors. However, the low adjusted R-squared suggests that there may be other factors driving the excess returns of the portfolio.

4.6 A modified rule: SaaS Investing Rule of 65

Despite the effectiveness of the Rule of 40 as a stock selection criterion, some value-oriented practitioners may criticise the rule for its lack of consideration for the valuation of stocks. In particular, the identification of the value premium within stock returns was already exposed by Fama and French in their seminal 1992 study. They observed that, throughout the period extending from 1963 to 1990, stocks within the United States exhibiting elevated book equity to market value ratios yielded higher average returns compared to those with diminished book-to-market ratios. This foundational observation concerning book-to-market ratios received further empirical support from the research conducted by Davis et al. (2000), which encompassed a comprehensive analysis over a nearly seven-decade span (1929-1997). Subsequent scholarly endeavours (Penman et al., 2005; Leibowitz, 2002; Nissim & Penman, 1999) have consistently demonstrated that investment strategies predicated on selecting stocks with lower valuation ratios are associated with the realisation of above-average returns on stock portfolios.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

While the majority of these investigations have predominantly employed price-to-earnings (P/E) or price-to-book (P/B) ratios as preferred metrics for valuation, Fisher (1984) introduced an alternative financial ratio, namely the market price-to-sales (P/S) ratio. This ratio, which quantifies the amount an investor is prepared to expend for each dollar of sales, has gained increasing prominence among investors for the purpose of stock selection in recent years. Fisher posited that the inherent stability of a company's sales relative to its earnings or book values renders the P/S ratio a more efficacious measure for assessing the robustness of the underlying business. He further contended that the P/S ratio serves as an adept indicator of a stock's market popularity.

According to Fisher (1984), stocks associated with companies that command high P/S ratios enjoy widespread popularity among investors; however, they are less likely to generate long-term, above-average returns due to their elevated stock prices in relation to sales. In contrast, stocks characterised by low P/S ratios are posited to have a higher likelihood of yielding long-term, above-average returns, especially in instances where there is an improvement in the company's performance, such as unforeseen increases in earnings or sales, which would significantly elevate the stock's attractiveness to investors. Moreover, an emphasis on sales enables investors to uncover investment opportunities among companies that, despite operating at a loss (thereby lacking P/E ratios due to negative earnings), exhibit low P/S ratios and hold promising growth prospects. This point is particularly pertinent to young SaaS companies.

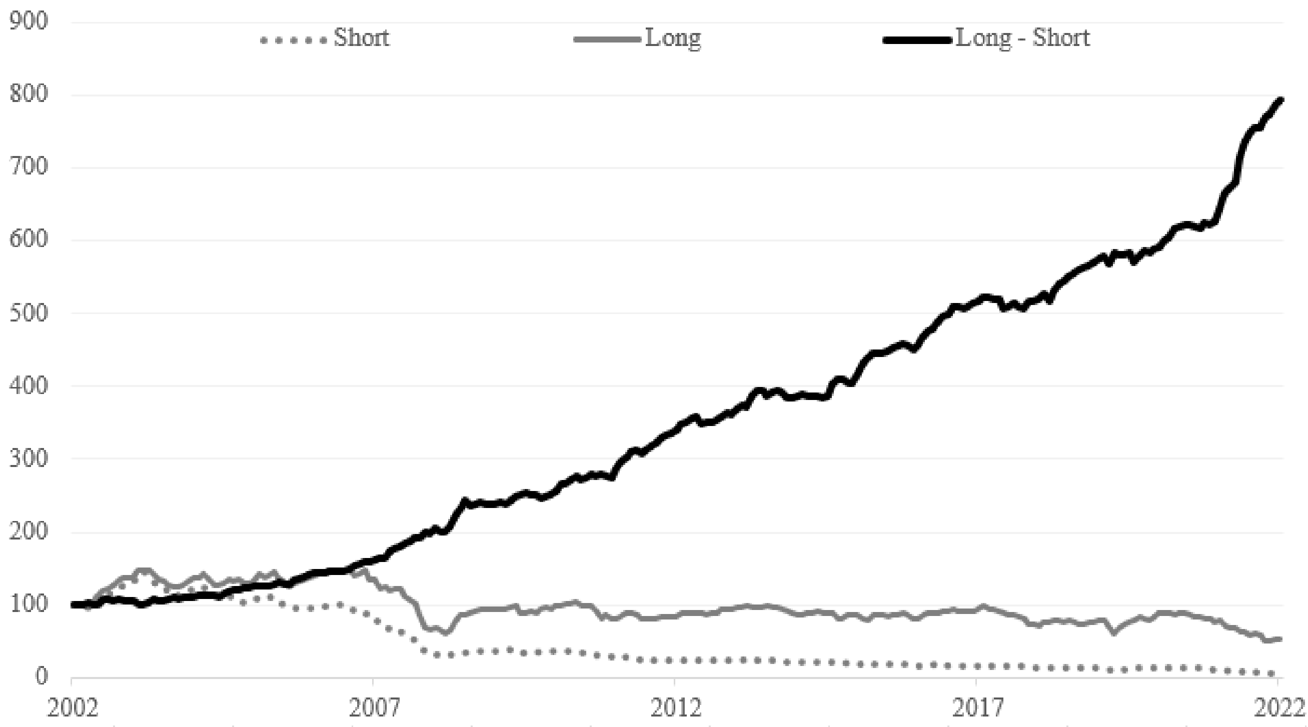
To incorporate the consideration of valuation in the rule, we propose a SaaS Investing Rule of 65 (SIR65), which is defined as follows:

$$\text{SaaS Investing Rule of 65} = \text{Sales growth over last year} + \text{EBITDA margin} + \text{Sales yield} \tag{2}$$

where Sales yield is defined as the inverted Price-to-Sales ratio.

The results of this proposed rule are presented in Panel E of Table 2. Compared to the Rule of 40, stocks that exceed our proposed rule deliver better returns at similar win rates, while stocks that fail the modified rule perform significantly worse with lower win ratios. The long-short portfolio also delivers significantly higher returns and win ratio when using the SIR65 as a stock selection criterion versus the Rule of 40. The cumulative returns of the long-minus-short portfolio that are shown in Figure 4 shows the more consistent positive return generation of the modified rule.

Figure 4: Time series plots of the cumulative returns of long, short and long-minus-short portfolios formed on the SaaS Investing Rule of 65 (January 2003 – December 2022)



Note: This chart shows the cumulative monthly returns of the long, short and long-minus-short portfolios formed on the SaaS Investing Rule of 65 (SIR65). The long portfolio consists of companies which satisfy the rule while the short portfolio consists of companies that fail the rule. Monthly median returns from January 2003 to December 2022 are used for the calculations.

4.7 Macroeconomic sensitivities

In order to gain a deeper comprehension of the macroeconomic sensitivities of the Rule of 40 and the SaaS Investing Rule of 65, we conduct two statistical analyses. First, we examine the long-short performance of these rules under varying macroeconomic conditions. Second, we perform stress testing to assess the robustness of these rules under extreme market scenarios.

4.7.1 Growth and inflation environments

Though there may be differing viewpoints on which macroeconomic dimensions are most crucial to examine, it is commonly accepted that economic growth and inflation exert the most significant influence on investment returns. Concurring with this widely held belief, our analysis focuses on these two fundamental macroeconomic factors.

In this study, we utilise the Citi Surprise Indices as measures of economic growth and inflation. These indices, developed by Citigroup, are objective and quantitative gauges designed to monitor the degree to which economic data releases diverge from market expectations. They offer a weighted historical mean of data surprises (actual releases versus Bloomberg survey median) for a range of key macroeconomic indicators. Specifically, we employ the Citi Economic Surprise Index and the Citi Inflation Surprise Index for both Developed and Emerging markets. Following the methodology of Ilmanen et al. (2014), we categorise these indices into binary "up" and "down" states by comparing the monthly value with the historical median, ensuring an equal distribution of observations across both states.

Our findings, as presented in Panel A of Table 5, evinced that the Rule of 40 typically exhibited a superior performance in "down" environments characterised by contracting growth or subdued inflation, achieving Sharpe ratios exceeding 1.0. This performance was notably superior to that observed in "up" environments, where the Sharpe ratios were generally less than half of those attained during "down" periods. Conversely, the SaaS Investing Rule of 65 demonstrated an improved performance in "up" environments marked by expanding growth and escalating inflation compared to its performance in "down" environments. However, it is noteworthy that the differences in the Sharpe ratios across both states were relatively narrow for this rule. Across all states of both macroeconomic factors examined, the SaaS Investing Rule of 65 consistently delivered higher Sharpe ratios in comparison to the Rule of 40.

Table 5: Macroeconomic sensitivities (January 2003 - December 2022)

Panel A: Hypothetical Sharpe ratios in growth and inflation environments

Environment	State	Rule of 40	SaaS Investing Rule of 65
Growth (Developed markets)	Up	0.451	2.003
	Down	1.174	1.703
Inflation (Developed markets)	Up	0.567	2.078
	Down	1.016	1.592
Growth (Emerging markets)	Up	0.430	2.118
	Down	1.186	1.562
Inflation (Emerging markets)	Up	0.388	2.148
	Down	1.140	1.555

Panel B: Stress testing using historical scenarios

Event	Start date	End date	Number of months	Rule of 40	SaaS Investing Rule of 65
Global financial crisis	30-Apr-08	28-Feb-09	10	6.268	13.690
Euro debt crisis	31-Mar-11	30-Nov-11	8	-4.812	2.776
Taper tantrum	30-Apr-13	31-Aug-13	4	5.804	3.765
Oil price decline	30-Jun-14	31-Dec-14	6	4.026	4.991
EM slowdown	31-May-15	30-Sep-15	4	-2.514	-1.039
Brexit referendum	31-May-16	30-Jun-16	1	0.360	0.499
Volatility spike	31-Aug-18	31-Dec-18	4	0.208	1.650
Covid pandemic	31-Jan-20	31-Mar-20	2	3.317	0.290
DM rate hike	31-Dec-21	30-Sep-22	9	3.981	5.673

4.7.2 Stress testing

We next conduct historical stress tests to quantify potential losses during periods of historical stress and to assess the resilience of the investment rules. This is accomplished by examining the influence of these historical events on the performance of the Rule of 40 and the SaaS Investing Rule of 65, thereby providing a robust evaluation of these strategies' capacity to withstand adverse market conditions.

In line with the approach adopted by Norges Bank Investment Management (2022), we select nine stress periods within our sample timeframe, including the Global Financial Crisis, which persisted for ten months until February 2009. As evidenced in Panel B of Table 5, during the majority of these episodes, both the Rule of 40 and the SaaS Investing Rule of 65 yielded positive returns. The Rule of 40 recorded negative returns in only two of these periods, while the SaaS Investing Rule of 65 experienced negative returns in just one. Notably, both rules manifested negative returns during the Emerging Markets (EM) slowdown from May to September 2015. While this could imply that the effectiveness of these rules is contingent on economic growth in emerging markets, our earlier analysis does not support this assertion. Across all these stress periods, the SaaS Investing Rule of 65 generally outperformed the Rule of 40, with the exceptions being the Taper Tantrum and the Covid pandemic.

4.8 Complementing the Rule of 40/65 with qualitative analysis

While the Rule of 40 and the suggested Rule of 65 have demonstrated efficacy in the selection of stocks within the SaaS sector, the inherently dynamic nature of the SaaS marketplace underscores the significance of qualitative factors in shaping the relevance and effectiveness of these benchmarks. A nuanced integration of such qualitative dimensions with these financial metrics can furnish a more holistic perspective on the operational and strategic health of SaaS enterprises. In their extensive examinations of the scholarly corpus, Floerecke and Lehner (2022) and Walther et al. (2012) identify several critical qualitative elements that merit consideration.

Paramount amongst these qualitative factors is management quality, with the expertise, vision, and execution prowess of the leadership team being pivotal to SaaS firm success. Possessing a profound comprehension of the SaaS model, competitive dynamics, customer needs, and technological trends is imperative for astute strategic decision-making and deftly steering the company through challenges while seizing opportunities.

Continuous product innovation is another critical factor, necessitating substantial investment in R&D, vigilant monitoring of customer needs and market shifts, and consistent updates to maintain a competitive edge over stagnant offerings. Market position constitutes a key advantage, with an established brand, sizeable share and deep competitive intelligence enabling robust market defence, share gains, stronger pricing power, and incisive competitive strategies.

Effective customer acquisition and retention strategies, including judicious marketing, tailored sales approaches, attractive pricing, and exceptional customer experience, are paramount for cost-effective customer management and sustained growth. Concurrently, scalability through secure, adaptable infrastructure is crucial for seamlessly handling demand fluctuations and capitalising on growth. Robust interoperability, leveraging standard protocols and architectures, fosters seamless integration with customers' IT ecosystems, driving adoption.

A culture promoting innovation, agility, collaboration, and employee engagement is valuable for attracting top talent and nurturing an environment conducive to developing market-leading solutions. Moreover, harnessing data analytics can yield valuable insights for enhancing offerings, experiences, pricing strategies, and informed decision-making. Ensuring regulatory compliance, data privacy, and robust cybersecurity is imperative for building customer trust and avoiding penalties.

Ultimately, he capacity to adapt products, processes, and business models to the rapidly changing SaaS landscape is indispensable for sustained competitiveness and seizing market opportunities. By incorporating an analysis of these qualitative factors alongside the quantitative benchmarks of 40/65, investors can enhance their ability to distinguish between potentially successful and unsuccessful SaaS enterprises.

5. Conclusion

The Rule of 40 has emerged as a valuable financial guideline for stock selection in the software and technology industry. By considering the balance between revenue growth rate and profit margin, the Rule of 40 offers a comprehensive assessment of a company's financial health and growth potential. This paper explores the effectiveness of the Rule of 40 as a stock selection criterion, providing insights into its application and implications for investors and analysts.

The analysis and findings of this study demonstrate that the Rule of 40 adds value and delivers a moderately high Sharpe ratio as a stock selection tool within the SaaS universe. We also propose a modified rule, which we term the SaaS Investing Rule of 65, that encompasses valuation considerations. Our findings suggest that our modified rule outperforms well in identifying relative winners and losers within the SaaS space and achieves high Sharpe ratios.

The effectiveness of the Rule of 40 and our proposed SaaS Investing Rule of 65 as stock selection criteria in the SaaS industry raises practical implications for investors and analysts. We identify four uses for the rules. Firstly, they can serve as initial screening tools for identifying SaaS companies with a balanced financial profile. By applying the rules, investors can filter out companies that may have potential issues with either growth or profitability and narrow down the investment universe to companies that exhibit strong growth prospects combined with healthy profit margins. Secondly, the rules, being quantitative assessments of companies' attractiveness as investment opportunities, can also be complemented with qualitative analyses. Factors such as competitive positioning, product differentiation, management team, and market dynamics should be considered to gain a comprehensive understanding of a company's long-term prospects. Combining the rules with qualitative analysis can enhance the investment decision-making process. Thirdly, the rules are particularly suited for investors with a long-term investment horizon. SaaS companies often prioritise growth and may temporarily prioritise market share over immediate profitability. Investors with a long-term perspective can therefore leverage the rules to align their investment strategies with the growth potential of the SaaS industry.

Further research and exploration are warranted to investigate the usefulness of these rules in other sectors that are also dominated by network effects, such as the ecommerce and internet industries.

In conclusion, the Rule of 40 and SaaS Investing Rule of 65 serve as valuable additions to the toolkit of investors and analysts seeking to identify relative SaaS stock winners and losers. By incorporating the rules into investment strategies, stakeholders can enhance their decision-making processes and align their portfolios with the dynamic landscape of the software and technology industry.

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INDEPENDENT DIRECTORS AND FIRM VALUE: NEW EVIDENCE FROM THE 2023 REGULATORY REFORM IN CHINA

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Abstract

This paper explores the "Measures for the Management of Independent Directors of Listed Companies" announced on August 4, 2023, for Chinese listed firms. We find that firms failing to meet the criteria in the Measures suffer losses in the stock market. The 2023 Measures exogenously increase the demand for qualified independent directors and incur high search costs for firms facing more labour market constraints.

Keywords: Regulatory Shock, Corporate Governance, Independent Directors, Firm Value

1. Introduction

On August 4, 2023, the China Securities Regulatory Commission (CSRC) officially released the "Measures for the Management of Independent Directors of Listed Companies" (hereinafter referred to as the Measures), which will be implemented on September 4, with a one-year transition period from the implementation[1]. This regulatory reform attracted enormous attention from financial market participants and occupied the headlines of most Chinese financial social media. The Measures aim to promote the formation of a more scientific and reasonable independent director system, which consists of six chapters and 48 articles, clarifying the qualifications and appointment and removal procedures of independent directors, the duties and performance methods of independent directors, performance guarantees, legal responsibilities, and transitional arrangements.

We compare the 2023 new Measures with the 2022 Rules (Rules for the Independent Directors of Listed Companies, effective from January 5, 2022)[2]. The major accessible changes in independent director requirement and corporate board structure that we can track using the current disclosed data include that (1) independent directors are required to have work experience related to either laws, accounting, or economics for at least five years; (2) independent directors can adjunctly serve

[1] http://english.sse.com.cn/news/newsrelease/c/5725012.shtml

[2] We show the evolution of the independent director system in Appendix Table 3

no more than three companies; (3) corporate boards are required to implement cumulative voting when there are two and more independent directors[3].

The Board of Directors, at the apex of internal control systems, is charged with advising and monitoring management and has the responsibility to hire, fire, and compensate the senior management team (Jensen, 1993). International studies for countries such as the UK, Korea, and India consistently show a positive correlation between board independence and firm performance (e.g., Black and Khana, 2007; Choi et al., 2007; Dahya & McConnell, 2007; Dahya et al., 2008; Aggarwal et al., 2009; Bruno & Claessens, 2010; Black & Kim, 2012). In a study of Chinese listed firms, Liu et al. (2015) exploit the issuance of "The Guideline for Introducing Independent Directors to the Board of Directors of Listed Companies", which was introduced in 2001 by the CSRC. They find that independent directors have an overall positive effect on firm operating performance in China.

This paper investigates whether the 2023 Measures have an effect on firm value. We conduct an event study on the stock market reaction around the day of the announcement of the Measures. We use the pre-announcement cross-sectional variation in board structure to compare the difference in the stock price reaction for firms with a more versus less scientific and reasonable independent director system according to the Measures.

Our empirical analysis focuses on 4,431 Chinese listed firms by the end of 2022. We extracted information on the corporate board of directors from CSMAR. For each firm in our sample, we identify whether it has independent directors who adjunctly serve more than three firms; whether it has independent directors without an economics, accounting, or law background; whether it has two or more independent directors and no cumulative voting. We then construct a count variable, Total, which aggregates the three indicators above, with a higher value indicating a less scientifically independent board system. On the days after the announcement of the Measures, we find that the cumulative abnormal stock return for firms failing to meet more criteria suffer more losses. In terms of economic magnitude, firms' 6-day cumulative abnormal returns (CAR [0, +5]) decrease by 15.3 basis points, when firms fail to meet an additional criterion in the 2023 Measures using the industry and province fixed effects. The results are robust using different event windows and fixed effects combinations[4].

We next examine the individual effect of each criterion on firm value. We conjecture that independent directors are scarce human capital, and the Measures can impose high costs and constraints on searching for qualified independent directors. We find that firms having independent directors without an economics, accounting, or law background have the most negative cumulative abnormal returns. Failing to meet the other two criteria does not significantly affect the stock price. The results are intuitive because ensuring all independent directors have an economics, accounting, or law background tends to be more costly than satisfying the other criteria.

We further examine the underlying mechanisms through which the Measures affect firm value. Prior studies on the costs of labour adjustment in the labour economics literature argue that when a firm adjusts its labour demand, it incurs the costs of firing, search, selection, hiring, and training, especially for highly skilled labour (Ghaly et al., 2017). We conjecture that independent directors are valuable and scarce human capital from the following aspects.

First, several academic studies document that qualified independent directors are highly skilled labour and scarce human resources to firms. For example, Li et al. (2022) show that academy fellow independent directors are scarce innovative human capital for Chinese firms. Cheng and Sun (2019)

[3] Though there are several additional regulations and policies in the new *Measures* that affect the independent director system for Chinese listed firms, we only focus on the above three significant changes in this study, because they allow us to identify firms that meet and do not meet these requirements before the reform.

[4] We report the results of robustness checks in Appendix Table 2.

show that government official independent directors are scarcer to Chinese firms. Du et al. (2018) study the market for auditors and found that signing auditors who are statutorily required to have a certain level of education and professional experience are a relatively scarce form of human capital in the Chinese audit market. Their findings also suggest that highly skilled labour with auditing experience can be scarce and valuable in the Chinese independent director market.

Second, we also argue that certain levels of education or professional experiences themselves do not make a qualified director, as the skills necessary to effectively communicate with the management team in a timely manner and obtain information to advise and monitor the managers are equally or more important. The general skill sets of performing director duties reduce the potential pool of director candidates. Consistent with this argument, Minghua Gao, the director of Research Centre for Corporate Governance and Enterprise Development (CGED), said that human resources for independent directors who are capable and faithfully perform their duties are still relatively scarce in China.[5]

Third, the insufficient coverage of liability insurance for independent directors can prevent qualified candidates from actually becoming independent directors. According to an article posted on the Chinese government website, since directors' liability insurance was introduced into the securities market in 2002, more than 500 listed companies have purchased directors' liability insurance, with an average annual insurance coverage rate of only 2%.[6]

Lastly, by the end of August 2023, the independent director information database displays the basic information of only 11,000 current independent directors across the entire market.[7] The pool is small given that there are around 5,000 listed firms in China. Taken together, we argue that it is likely that qualified independent directors are scarce human capital to firms in the Chinese financial market.

Since we conjectured that the Measures impose a greater constraint and higher costs for firms to meet the mandated board structure requirements, by replacing unqualified independent directors with qualified ones, firms with lower searching costs and higher propensities to attract qualified independent directors are expected to be less affected by the Measures. Consistent with our conjecture, we find that the effect of Measures on stock market reactions becomes stronger when firms face higher competition in the labour market for independent directors, weaker when firms possess greater market shares within industries, and weaker when firms are supported by more institutional investors.

This paper adds to the labour economics literature on the costs of labour adjustment. When a firm adjusts its labour demand, it incurs the costs of firing, search, selection, hiring, and training, which are economically significant and increase with the skill level of the labour force (e.g., Shapiro, 1986; Ghaly et al., 2017). Furthermore, searching for, hiring, and training new employees is more costly for jobs that require workers with advanced skills who are usually in shorter supply (e.g., Dolfin 2006). In this paper, we study a type of highly skilled labour, independent directors, by exploiting a regulatory reform imposing exogenous high costs of labour adjustment. Our findings contribute to the existing literature by focusing on the market for independent directors. Our results show that firms facing greater labour market competition and more constraints in searching for independent directors bear more losses in shareholder value.

This paper also contributes to the literature on independent boards. Theoretically, independent directors have duties to perform their monitoring and advising functions, which have important value

5 https://www.nbd.com.cn/articles/2023-04-14/2761011.html

6 https://www.gov.cn/zhengce/2023-04/15/content_5751630.htm#:~:text=%E8%87%AA2002%E5%B9%B4%E8%91%A3%E4%BA%8B,%E4%BF%9D%E6%AF%94%E4%BE%8B%E4%BB%85%E4%B8%BA2%25%E3%80%82

7 https://m.huanqiu.com/article/4EG0GgiTrTQ

implications for firms. (e.g., Danielson and Karpoff, 1998; Masulis and Mobbs, 2011; Liu et al., 2015). Expertise of independent directors affects board monitoring effectiveness and firm performance (e.g., Wang et al., 2015; Giannetti et al., 2015). The stock market reacts negatively to the death of independent directors due to a reduction in board independence and the loss of individual skills and competence (Nguyen & Nielsen, 2010). Using a newly introduced regulatory reform on independent directors in China, we find that firms suffer negative stock market reactions when they are mandated to replace unqualified independent directors. We provide new evidence that having unqualified independent directors can destroy firm value.

2. Data

Our sample includes all Chinese listed firms by the end of 2022. We use the Fama-French three factors model to calculate firms' cumulative abnormal returns. We apply an estimation window [-110, -10] and remove observations with less than 70 days in the estimation period. Our event day is August 4, 2023, the date when the Measures were first released by the CSRC.

We collect information about the firms' independent directors from CSMAR and organise the information in the following ways. First, we extract the occupational backgrounds of independent directors and filter those that lack economic, accounting, and law related experience. Second, we search for firms that do not establish audit committees. Third, we extract information about the cumulative voting system from each firm's working system for independent directors. We construct Adjunct Directors (dummy), which equals one if any independent directors in a firm adjunctly serve more than three firms; No EAL Background (dummy), which equals one if any independent director in a firm has no economic, accounting, or law related experience; No Cumulative Voting (dummy), which equals one if a firm does not have a cumulative voting system when it has at least two independent directors.

We compare the 2023 Measures with the 2022 Rules and find that most changes are new items, which uniformly affect all Chinese listed firms. Moreover, we also document that some changes are unmeasurable using the currently available data, which is a limitation of our paper[8]. To mitigate the concern, we examine the effect of each of the three measurable changes on CARs separately, as it is unlikely that the unmeasurable changes are highly correlated with each of the three measurable changes.

We combine firm-level cumulative abnormal returns with information on independent directors. We also collect firm characteristics from CSMAR as control variables. We follow Zhu et al. (2016) to include Firm Size, Book Leverage, ROA, Book to Market, Capital Expenditure, Board Size, Independent Board, Board Ownership, and SOE. Our final sample contains 4,431 non-financial firms. Table 1 shows summary statistics for our sample. The variable definitions are illustrated in Appendix Table 1. We find that 25.6%, 72.2%, and 89.3% of the firms in our sample do not meet the new requirements on adjunct directors, EAL background, and cumulative voting, respectively.

[8] Due to constraints related to data disclosure, some changes are difficult to quantify. For example, new regulations stipulate that independent directors cannot provide third-party services to controlling shareholders, and members of the audit committee must be non-executive directors.

Table 1: Summary Statistics

Variable	N	Mean	SD	P50	Max	Min
Total	4431	1.871	0.714	2	3	0
Adjunct Directors (dummy)	4431	0.256	0.436	0	1	0
No EAL Background (dummy)	4431	0.722	0.448	1	1	0
No Cumulative Voting (dummy)	4431	0.893	0.309	1	1	0
Number of Firms by City	4431	3.932	1.573	4.078	5.956	0.693
Number of Firms by Industry	4431	4.878	1.088	5.017	6.258	0.693
Market Share in Industry	4428	0.0150	0.0590	0.002	1	0
Institutional Ownership	4430	41.80	25.15	41.61	231.8	0
Firm Size	4431	9.669	0.577	9.579	12.43	8.004
ROA	4431	0.0320	0.0670	0.0360	0.220	-0.217
Book Leverage	4431	0.398	0.203	0.386	0.897	0.051
Capital Expenditure	4431	0.0500	0.0470	0.0360	0.221	0
Book-to-market	4431	0.669	0.248	0.678	1.246	0.141
Board Size	4431	8.213	1.564	9	18	4
Independent Board	4431	3.065	0.526	3	8	1
Board Ownership	4431	5.716	3.067	7.240	9.605	0
SOE	4425	0.269	0.444	0	1	0

Note: This table presents summary statistics of the sample.

3. Empirical results

3.1 Stock market reactions of firms to the announcement of the 2023 Measures

We investigate firms' stock market reactions after the 2023 Measures. We calculate the CAR using the Fama-French three factor model (Fama & French, 1993) and examine whether the stock market reacts differently for firms facing different levels of constraints to meet the criteria. We compute a 6-day window CAR from the event day to five days after (CAR [0, +5]) for our main analysis. We chose this window because it covers an entire week after the regulatory reform, which allows us to observe the weekly stock market reactions of Chinese listed firms. We use both the univariate analysis and regression with fixed effects. Specifically, we estimate the following model:

$$CARs_i = \alpha + \beta_1 Total_i + \beta_2 X_i + FEs + \varepsilon_i \, , \tag{1}$$

where CARs is a firm's CAR after the announcement of the Measures. Total is the count of criteria in the Measure that a firm fails to meet. X is a list of firm controls, and FEs can be various combinations of fixed effects. Standard errors are clustered at the provincial level.

Panel A of Table 2 reports the univariate analysis comparing the mean CAR with zero, grouped by the number of criteria a firm fails to meet. We show an average CAR for firms meeting all criteria before the regulatory reform of 0.895 percent, which is not statistically significant. The average CARs [0, +5] for firms that fail to meet one, two, and three criteria are -0.266, -0.425, and -0.744, respectively, all significantly smaller than zero. The findings of the univariate analysis suggest that firms that would be more severely affected by the Measure experienced more losses in the days after the announcement.

Panel B of Table 2 reports the regression analysis. Column (1) does not use fixed effects. Columns (2) – (5) apply province fixed effects, industry fixed effects, province fixed effects and industry fixed effects, and province-industry fixed effects, respectively. Including province and industry fixed effects helps address the concern that province and industry heterogeneity may drive the results. We show that the estimate coefficients on Total are -0.266, -0.280, -0.193, -0.207, and -0.202 in Columns (1) – (5), respectively, all negative and statistically significant. These results are also economically sound. When a firm fails to meet one additional criterion mandated in the Measure, it is estimated to suffer average losses of 19.3 – 28.0 basis points in the five days after the announcement. In tests reported in the appendix, we use alternative event windows for robustness checks, and the results are similar.

Table 2: Baseline Results

Panel A. Univariate Analysis

	Total = 0	Total = 1	Total = 2	Total = 3
Mean (%)	0.895	-0.266*	-0.425***	-0.744***
	(0.856)	(-1.931)	(-3.164)	(-5.419)
Observations	117	1101	2449	764

Panel B. Regression Analysis

	CARs [0, +5]				
	(1)	(2)	(3)	(4)	(5)
Total	-0.261**	-0.283***	-0.198**	-0.208**	-0.204*
	(-2.739)	(-2.854)	(-2.049)	(-2.140)	(-1.947)
Firm Size	-0.950***	-1.101***	-1.200***	-1.241***	-1.223***
	(-4.854)	(-6.550)	(-7.936)	(-8.856)	(-7.906)
ROA	-2.229*	-2.980**	0.181	0.218	-0.548
	(-1.786)	(-2.400)	(0.158)	(0.201)	(-0.526)
Book Leverage	-1.317***	-1.921***	0.035	0.062	-0.105
	(-3.266)	(-4.282)	(0.075)	(0.121)	(-0.192)
Capital Expenditure	-5.863***	-7.413***	-4.772**	-4.598**	-4.610*
	(-2.806)	(-3.511)	(-2.371)	(-2.252)	(-1.941)
Book-to-market	0.675*	0.122	0.945***	1.006***	0.890**
	(1.920)	(0.400)	(3.099)	(3.349)	(2.555)
Board Size	-0.059	-0.079	-0.076	-0.062	0.001

	(-1.074)	(-1.486)	(-1.390)	(-1.119)	(0.013)
Independent Board	0.481***	0.538***	0.482**	0.437**	0.311
	(2.781)	(2.883)	(2.460)	(2.284)	(1.574)
Board Ownership	0.064**	0.083**	0.052**	0.052**	0.046
	(2.063)	(2.694)	(2.225)	(2.211)	(1.495)
SOE	0.616**	0.507*	0.421*	0.328	0.228
	(2.535)	(1.784)	(1.798)	(1.361)	(0.817)
Constant	8.328***	10.309***	9.899***	10.293***	10.205***
	(4.830)	(6.331)	(6.915)	(7.599)	(6.707)
Province FE	No	Yes	No	Yes	No
Industry FE	No	No	Yes	Yes	No
Province-Industry FE	No	No	No	No	Yes
Observations	4425	4425	4423	4423	4028
Adjusted R^2	0.023	0.050	0.169	0.172	0.162

Note: This table demonstrates the baseline results examining the impact of failing to meet criteria on the stock market. Panel A provides the results of univariate tests by the number of criteria firms fail to meet. Panel B presents the results of regression analysis, where the independent variable is the number of criteria that firms do not meet and the dependent variable is firms' CARs [0, +5]. Column (1) includes firm controls but not fixed effects; column (2) adds province fixed effects; column (3) adds industry fixed effects; column (4) uses both industry and province fixed effects; column (5) uses province-industry fixed effects. See the Appendix for detailed variable definitions. Heteroskedasticity-robust standard errors are adjusted for clustering at province level. The t-statistics are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

3.2 Individual effect of each criterion on stock market reaction

In this section, we examine the individual effect of each criterion mandated by the Measures to identify the criteria affecting the stock market reactions most. We include each of the three dummy variables, Adjunct Directors (dummy), No EAL Background (dummy), and No Cumulative Voting (dummy) in the regression model separately.

Table 3 shows that the estimated coefficient on No EAL Background (dummy) is -0.419, which is significantly negative. The estimate coefficients on Adjunct Directors (dummy) and No Cumulative Voting (dummy) are statistically insignificant. In column (4), we include all dummies in the regression and find similar results. Ensuring all independent directors have an economic, accounting, or law background is expected to impose greater constraints and higher costs in searching for qualified independent directors. Moreover, the insignificant coefficient on No Cumulative Voting (dummy) is also consistent with the prior studies on the Chinese listed firms, which document the no effect of cumulative voting on firm performance in China (e.g., Xi and Chen, 2014; Chen et al., 2015). These findings also have policy implications for the effectiveness of the 2023 Measures. It highlights the areas that the financial market reacts most among the regulatory changes in the Measures.

Table 3: Individual Effect of Each Criterion on Stock Market Reaction

	CARs [0, +5]			
	(1)	(2)	(3)	(4)
Adjunct Directors (dummy)	-0.017			-0.012
	(-0.089)			(-0.061)
No EAL Background (dummy)		-0.419***		-0.418***
		(-3.429)		(-3.426)
No Cumulative Voting (dummy)			-0.171	-0.165
			(-0.659)	(-0.636)
Firm Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4423	4423	4423	4423
Adjusted R^2	0.169	0.171	0.169	0.172

Note: This table provides the regression results examining the relation between each criterion and stock market reactions. The dependent variable is CARs [0, +5]. The independent variables are Adjunct Directors (dummy), No EAL Background (dummy), and No Cumulative Voting (dummy) in columns (1) – (3), respectively. In column (4), we include all criteria in the regression. Industry fixed effects and province fixed effects are added to all regressions. See the Appendix for detailed variable definitions. Heteroskedasticity-robust standard errors are adjusted for clustering at province level. The t-statistics are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

3.3 Mechanism - Labor Market Constraints

We investigate the economic mechanisms of the impact of the Measures on firm value. As mentioned earlier, the Measures exogenously push up the demand for qualified independent directors. Thus, we expect that stock market reactions are more pronounced when a firm faces greater labour market competition for independent directors. We measure a firm's labour market competition in several ways. First, we calculate the total number of listed firms in a firm's headquarter city and industry as proxies for the demand for independent directors in the headquarter city and industry, respectively. We expect that the competition for qualified directors in high-demand cities and industries will be more intense. Second, we calculate a firm's market share within the industry as large firms attract and retain more-capable workers (Idson & Oi, 1999). We argue that a firm's competitiveness can provide advantages in attracting qualified independent directors, and the industry leaders would be least affected by the Measures. Third, we calculate the total institutional ownership of a firm. Institutional investors can provide helping hands and share connections with their portfolio firms (Jiao, 2022). We argue that firms with high institutional ownership would get easier access to qualified independent directors and be least affected by the regulatory reform. We interact Total with these moderators and estimate the following model:

$$CARs_i = \alpha + \beta_1 Total_i \times Moderator + \beta_2 Total_i + \beta_3 Moderator + \beta_4 X_i + FEs + \varepsilon_i, \quad (2)$$

where CARs is a firm's CAR after the announcement of the Measures. Total is the count of criteria in the Measure that a firm fails to meet. Moderator can be Number of Firms by City, Number of Firms by Industry, Market Share in Industry, or Institutional Ownership.

Table 4 reports the cross-sectional analysis results. The coefficients on Total × Number of Firms by City (log) and Total × Number of Firms by Industry (log) are significantly negative, which suggests that being in a more competitive labour market for independent directors amplifies the effect of Measures on firm value. The coefficients on Total × Market Share in Industry and Total × Institutional Ownership are significantly positive, suggesting that industry leaders and firms with institutional support could reduce the cost and constraint of searching for qualified independent directors. The findings provide supporting evidence for the labour market constraints hypothesis.

Table 4: Cross-sectional Analyses

	CARs [0, +5]				
	(1)	(2)	(3)	(4)	(5)
Total	0.493**	0.477**	-0.240**	-0.561*	0.164
	(2.120)	(2.057)	(-2.207)	(-1.972)	(0.477)
Total × Number of Firms by City (log)	-0.174***				-0.176***
	(-3.258)				(-2.935)
Total × Number of Firms by Industry (log)		-0.140***			-0.107*
		(-3.249)			(-1.970)
Total × Market Share in Industry			3.522***		0.117*
			(3.957)		(1.736)
Total × Institutional Ownership				0.009*	0.009*
				(1.723)	(1.759)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4423	4423	4420	4422	4419
Adjusted R^2	0.172	0.171	0.172	0.173	0.178

Note: This table provides the results of a series of cross-sectional analyses. The dependent variable is CARs [0, +5]. The moderator variable in column (1) is the number of listed firms within each city in this sample; the moderator variable in column (2) is the number of listed firms in each industry in this sample; the moderator variable in column (3) is the market share of a firm in the industry where the firm operates; and the moderator variable in column (4) is the percentage of the firm's shareholding by institutional investors. In column (5), we include all interaction terms[9]. All regressions control for province and industry fixed effects. See the Appendix for detailed variable definitions. Heteroskedasticity-robust standard errors are adjusted for clustering at province level. The t-statistics are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

[9] Since *Number of Firms by Industry (log)* and *Market Share in Industry* are highly correlated, there is a multicollinearity issue. To address the issue, we orthogonalize *Market Share in Industry* with respect to *Number of Firms by Industry (log)* based on a modified Gram–Schmidt procedure, and include the orthogonalized *Market Share in Industry* in column (5).

4. Conclusion

In this paper, we exploit the stock market reaction to a 2023 regulatory reform on independent directors in China. We find robust evidence that firms meeting fewer criteria in the Measures suffer greater losses in the stock market. Among the criteria, establishing the audit committee and mandating all directors to have an economic, accounting, or law background affect the stock price most. We also show that firms facing more intense labor market competition are more affected and firms that are leaders in their industry and have more institutional support are less affected. These findings suggest that the 2023 Measures exogenously increase firms' demand for qualified independent directors and firms facing more labour market constraints are more adversely affected by the reform.

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Appendix

Appendix Table 1: Variable Definitions

Variable	Definition	Source
Adjunct Directors (dummy)	Dummy variable that takes the value of one if there is at least one independent director of the company who is also a director of more than three listed companies, and zero otherwise.	CSMAR
No EAL Background (dummy)	Dummy variable that takes the value of one if there is at least one independent director of the company who does not satisfy a professional background related to economics, finance, or law, and zero otherwise.	CSMAR
No Cumulative Voting (dummy)	Dummy variable that takes the value of one if the company has two or more independent directors and does not have a cumulative voting system, and zero otherwise.	CSMAR
Total	Number of violations of the above five criteria by the company.	CSMAR
Number of Firms by City (log)	The logarithm of total number of firms in each city in this sample.	CSMAR
Number of Firms by Industry (log)	The logarithm of total number of firms in each industry in this sample.	CSMAR
Market Share in Industry	Operating income of a firm divided by the total operating income of all firms in the same industry.	CSMAR
Institutional Ownership	Percentage of shares held by institutional investors in each company.	CSMAR
Firm Size	Natural logarithm of corporate total assets.	CSMAR
ROA	Net profit of the enterprise divided by total assets.	CSMAR
Book Leverage	Total debt divided by total assets.	CSMAR
Capital Expenditure	Capital expenditure divided by total assets.	CSMAR
Book-to-market	Book value of total assets divided by the market value of total assets.	CSMAR
Board Size	Number of corporate boards of directors.	CSMAR
Independent Board	Number of corporate independent directors.	CSMAR
Board Ownership	Logarithm of the total number of shares held by the board.	CSMAR
SOE	Dummy variable that takes the value of one if the firm is a state-owned enterprise and zero otherwise.	CSMAR

Appendix Table 2: Robustness Checks

Panel A. Baseline Results – Estimation Window [-110, -10]					
			CARs		
	[0, +1]	[0, +2]	[0, +3]	[0, +7]	[-5, +5]
No FE	-0.180**	-0.232***	-0.261***	-0.308**	-0.301***
(N=4424)	(-2.73)	(-3.47)	(-3.23)	(-2.71)	(-2.90)
Province FE	-0.186**	-0.236***	-0.266***	-0.334***	-0.302***
(N=4424)	(-2.72)	(-3.51)	(-3.31)	(-2.94)	(-2.88)
Industry FE	-0.148***	-0.170***	-0.203**	-0.255**	-0.226*
(N=4422)	(-3.22)	(-3.12)	(-2.72)	(-2.13)	(-2.02)
Province and Industry FE	-0.149***	-0.170***	-0.209***	-0.279**	-0.226*
(N=4422)	(-3.23)	(-3.11)	(-2.82)	(-2.33)	(-1.99)
Province - Industry FE	-0.137**	-0.154***	-0.192**	-0.226	-0.241*
(N=4027)	(-2.73)	(-3.00)	(-2.61)	(-1.59)	(-1.90)

Panel B. Individual Effect – Estimation Window [-110, -10]					
			CARs		
	[0, +1]	[0, +2]	[0, +3]	[0, +7]	[-5, +5]
Adjunct Directors (dummy)	-0.065	-0.07	-0.08	-0.127	0.006
	(-0.615)	(-0.473)	(-0.499)	(-0.582)	-0.037
No EAL Background (dummy)	-0.172*	-0.237***	-0.374***	-0.597***	-0.557***
	(-1.923)	(-2.812)	(-4.103)	(-4.069)	(-3.023)
No Cumulative Voting (dummy)	-0.288	-0.285	-0.253	-0.217	-0.103
	(-1.385)	(-1.558)	(-1.431)	(-0.664)	(-0.289)
Firm Controls	Yes	Yes	Yes	Yes	Yes

Province and Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4423	4423	4423	4423	4423

Panel C. Baseline Results – Estimation Window [-265, -10]

	CARs				
	[0, +1]	[0, +2]	[0, +3]	[0, +7]	[-5, +5]
No FE	-0.163**	-0.218***	-0.236***	-0.305***	-0.279**
(N=4424)	(-2.55)	(-3.34)	(-2.99)	(-2.83)	(-2.69)
Province FE	-0.169**	-0.222***	-0.241***	-0.332***	-0.281**
(N=4424)	(-2.57)	(-3.39)	(-3.07)	(-3.04)	(-2.63)
Industry FE	-0.140***	-0.163***	-0.190**	-0.250**	-0.214*
(N=4422)	(-3.05)	(-3.03)	(-2.61)	(-2.24)	(-1.94)
Province and Industry FE	-0.141***	-0.164***	-0.197**	-0.275**	-0.216*
(N=4422)	(-3.05)	(-3.02)	(-2.72)	(-2.44)	(-1.91)
Province - Industry FE	-0.133**	-0.151***	-0.184**	-0.209	-0.231*
(N=4027)	(-2.68)	(-2.94)	(-2.54)	(-1.53)	(-1.81)

Panel D. Individual Effect – Estimation Window [-265, -10]

	CARs				
	[0, +1]	[0, +2]	[0, +3]	[0, +7]	[-5, +5]
Adjunct Directors (dummy)	-0.059	-0.065	-0.075	-0.156	0.007
	(-0.560)	(-0.435)	(-0.475)	(-0.744)	-0.043
No EAL Background (dummy)	-0.167*	-0.237***	-0.362***	-0.562***	-0.541***
	(-1.787)	(-2.819)	(-4.016)	(-3.807)	(-2.919)
No Cumulative Voting (dummy)	-0.267	-0.258	-0.214	-0.178	-0.066
	(-1.318)	(-1.438)	(-1.192)	(-0.558)	(-0.192)

Firm Controls	Yes	Yes	Yes	Yes	Yes
Province and Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4423	4423	4423	4423	4423

Note: This table presents the results of OLS regressions using alternative event windows, alternative estimation windows, and alternative fixed effects. Alternative event windows include [0, +1], [0, +2], [0, +3], [0, +7], and [-5, +5]. Panel A shows the robustness results for the baseline regressions using [-110, -10] estimation window. Panel B shows the robustness results for the tests examining the individual effect of each criterion using [-110, -10] estimation window. Panel C shows the robustness results for the baseline regressions using [-265, -10] estimation window. Panel D shows the robustness results for the individual effect using [-265, -10] estimation window.

Appendix Table 3: The Evolution of the Independent Director System

Date of Publication	The Name of the Regulation	Key Points
March,26,1999	《Opinions on Further Promoting the Standard Operation and Deepening Reform of Overseas Listed Companies》	Requirements for Overseas Listing
April,16,2001	CSRS《Guiding Opinions on Establishing an Independent Director System in Listed Companies》	Requirements for Establishing Independent Directors
December,7,2004	CSRS《Several Regulations on Strengthening the Protection of Rights and Interests of Public Shareholders in Listed Companies》	Improving the Independent Director System
January,1,2006	《The Company Law of the People's Republic of China (Revised in 2005)》	Legal Requirement for the Establishment of Independent Directors Clarified for the First Time
January,5,2022	CSRC《Rules on Independent Directors of Listed Companies》	Non-substantive Modification, Unification, Integration, Absorption
April,14,2023	State Council General Office《Opinions on Reforming the Independent Director System of Listed Companies》	Clarify Reform Tasks
August,4,2023	CSRS《Regulations on the Management of Independent Directors in Listed Companies》	Implement Reform Opinions, Elaborate on System Requirements

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CEO GENDER AND FIRM PERFORMANCE: EVIDENCE FROM THE COVID-19 PANDEMIC

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Abstract

The COVID 19 pandemic precipitated an unprecedented deceleration of economic activities and a stock market crash. The unparalleled shock and the altered risk attitudes present a distinctive opportunity to examine whether the well-established concept of the "glass ceiling" is indicative of latent gender differentials in company performance. Utilising US financial data, the study employs a range of methodologies to examine whether firms led by female CEOs exhibited the same performance as firms led by male CEOs during 2020-2021. Our empirical results confirm previous findings from the finance literature, as we neither find a systematic difference in returns to holding stock in female-led firms, nor a difference in accounting returns between female-led and male-headed firms.

Keywords: Firm performance, gender diversity, pandemic, excess returns

1. Introduction

There has been a renewed emphasis on the representation of women in leadership positions, which can be attributed to the significant progress women have achieved in this domain. Several studies show that gender diversity in leadership roles can serve as an effective alternative mechanism for bolstering corporate governance control. Notably from literature, Adams and Ferreira (2009) find that women have a significant impact on board governance and that the CEOs' turnover is more sensitive to stock return performance in companies with a higher proportion of women on their boards. Melero (2011) finds that a higher proportion of female executives in a firm has beneficial effects in employee feedback and development. Jurkus et al. (2011) suggest that increasing diversity in management has positive impact on firms with absence of strong external governance and Upadhyay and Zeng (2014) show that gender diversity can lead to better strategic decisions. Furthermore, Iseke and Pull (2019) find that female job seekers tend to be more attracted to firms with female executives holding a non-stereotypical position.

However, a significant lack of representation of women in high-level managerial positions and as CEOs (Hillman et al., 2007), as well as pay gender gaps, continue to exist, despite advancements in overall employment trends. Blau and Kahn (2017) provide a comprehensive literature review on systematic gender differentials in the labour market, and particularly the decline of the pay gender gap from 1980 to 2010. Carter et al. (2017), using a large sample of S&P 1500 firms between 1996-2010, show that female risk aversion as well as the lack of gender diversity on corporate boards, can contribute significantly to the observed pay gender gap. Flabbi et al. (2019) complement the findings by Carter al. (2017), showing a positive effect of female leadership on the top of the female wage distribution.

Vandegrift and Brown (2005) show that the differential risk attitude of gender may affect the financial decision-making process. Given that firm outcomes depend on executives' characteristics, such as risk attitude and management practices, there is research work focused on financial risk aversion of men and women. Specifically, evidence from the experimental economics literature suggests that women, on average, tend to be more financially risk averse than men (Eckel & Grossman, 2008; Croson & Gneezy, 2009; Charness & Gneezy, 2012). On the other hand, the findings by Doan and Iskandar-Datta (2020) support the notion that female top executives are as risk-averse as their male counterparts.

In terms of firm performance and the gender of senior leadership, the results are mixed. A few papers (Barua et al., 2010; Liu et al., 2016) focus on the earnings quality in relation to the gender of CFOs, showing significantly lower abnormal accruals. Huang and Kisgen (2013) document that firms with female executives are less likely to make acquisitions, but have higher announcement returns relatively to those by firms with male executives. Several studies examine the relationship of stock prices, stock market returns and market values as proxies of firm performance and the proportion of women among board members is used as a measure of female leadership (Wolfers, 2006; Gul et al., 2011; Khan & Vieito, 2013). Findings by Gul et al. (2011) suggest that board gender diversity improves stock price informativeness, with the relationship being stronger for firms with weak corporate governance. Wolfers (2006), analysing data from more than 3,000 publicly traded companies from the period 1992-2004, finds that the stock returns of companies with female CEOs are not statistically different from the stock returns of companies with male CEOs, implying that a CEO's gender may not have a significant impact on a company's stock performance. On the other hand, Kolev (2012) finds that female-led firms significantly underperform relative to male-led firms. The key methodological difference is that Kolev (2012) focuses on the return of a firm in a given month, instead of the average return of a portfolio of firms in the given month as in the paper of Wolfers (2006). Lastly, Khan and Vieito (2013), focusing on accounting returns, as measured by the return on assets (ROA), find that female-headed firms tend to perform better than male-led firms.

Furthermore, evidence regarding female leadership during disruptive times is scarce (Wu et al., 2021). In one of the few studies examining female leadership and firm performance during a crisis period, Palvia et al. (2015) document that smaller banks with female CEOs and board chairs were less likely to fail during the 2007–2010 subprime crisis. Another study by Tiscini et al. (2023), investigating Italian-listed firms during the COVID-19 pandemic, finds a positive effect of female leadership on firm performance, as measured by the return on assets (ROA).

Drawing upon past empirical evidence, our paper seeks to investigate disparities in the financial performance between companies led by female and male CEOs, during the COVID-19 pandemic. The implementation of economic lockdown measures, during this period, presented an unforeseen shock to global financial markets which experienced a significant decline. Specifically in the U.S., the stock market reached its highest point in mid-February of 2020, followed by a significant decrease of about 30% within a span of just one month. This unparalleled shock has likely altered the risk attitude of financial decision makers (Heo et al., 2021). Consequently, the pandemic years present a unique crisis period prompting for a reassessment of the CEO gender gap in firm returns.

The objective of our paper is threefold: first, we contribute to the existing body of literature on gender and firm performance; second, we try to expand upon the recent literature on COVID-19 and its impact on businesses; third, we present new evidence related to the role of female leadership in times of crisis. We accomplish this by analysing the performance of female and male-led 1500 S&P firms during the COVID-19 pandemic. Our results reveal that female-headed firms did not outperform male-led firms during the pandemic and are robust in terms of stock market returns (stock market performance) and in terms of operating performance (Return on Assets, Gross Profit Margin and Growth of Sales), in both time series and in the cross-section.

The paper is organised as follows: Section 2 describes the data and explains the empirical methodology. Section 3 presents and analyses the results. Section 4 concludes.

2. Data and Methodology

2.1 Data

Table 1 presents the Summary Statistics of the variables in our study. The methodologies utilised are described in detail in the rest of this section.

Table 1: Summary statistics

	Obs.	Mean	SD	25%	Median	75%
Panel A: Variables 2020						
Daily excess return of zero-investment portfolio	253	0.12%	2.80%	-0.91%	0.12%	1.33%
Mean daily excess return	1314	0.10%	0.19%	0.01%	0.07%	0.17%
Annual abnormal return	1314	8.52%	49.42%	-15.16%	4.88%	27.33%
ROA	1316	0.092	0.104	0.036	0.09	0.139
Gross Profit Margin	1316	0.392	0.389	0.226	0.379	0.599
Growth of Sales	1317	-0.011	0.261	-0.11	-0.022	0.08
CEO_Gender	1317	0.944	0.233	1	1	1
Profitability	1316	0.009	0.365	-0.007	0.056	0.129
ROE	1259	0.019	1.307	-0.011	0.079	0.159
Leverage	1316	0.644	0.261	0.479	0.649	0.813
Cash Ratio	1092	1.112	3.382	0.257	0.532	1.073
Size	1317	3.397	0.699	2.926	3.358	3.858
Advertising	1316	0.013	0.035	0	0	0.011
Panel B: Variables 2021						
Daily excess return of zero-investment portfolio	252	-0.02%	0.46%	-0.29%	-0.05%	0.26%
Mean daily excess return	1451	0.12%	0.24%	0.04%	0.11%	0.18%
Annual abnormal return	1451	-1.77%	60.91%	-24.89%	-7.86%	14.85%
ROA	1355	0.122	0.114	0.06	0.11	0.168
Gross Profit Margin	1351	0.427	0.429	0.252	0.397	0.601
Growth of Sales	1216	0.243	0.837	0.04	0.138	0.266
CEO_Gender	1451	0.934	0.248	1	1	1
Profitability	1356	0.066	0.543	0.033	0.088	0.168
ROE	1307	0.19	0.657	0.06	0.131	0.235
Leverage	1356	0.63	0.235	0.46	0.635	0.793
Cash Ratio	1139	1.046	1.864	0.241	0.579	1.154
Size	1357	3.37	0.708	2.889	3.328	3.849
Advertising	1356	0.012	0.033	0	0	0.01

Note: Table 1 reports the summary statistics for the variables utilised in the study.

Due to their significant role in the organisation, we concentrate on CEOs. Data on CEO gender is available from the EXECUCOMP database. We gather information on CEO gender from 2020 and 2021, applying the following restrictions: we sort firms based on CEO gender in December 2019 (December 2020) for the next 12 months and exclude firms where the CEO gender changed during 2020 (2021); we remove observations of CEOs not receiving any compensation; we do not include CEOs who did not receive salary or bonus during these years. Women hold 5.6% - 6.6% of CEO positions in the sample years.

We retrieve daily and annual stock data from Capital IQ North America Daily (Compustat/CRSP, WRDS), for the years 2020 and 2021. To calculate stock returns, we adjust prices for dividends through the price adjustment factor (AJEXDI) and the daily multiplication factor (TRFD). In the case of dual listed firms, we keep only the security of the firm with the highest market capitalisation. A key variable of interest in firm-level analysis is leverage, which is difficult to compare between non-financial and financial firms (Fama & French, 1992). Therefore, and in accordance with standard practice in finance research, for our firm-level study, we exclude financial companies. Next, we estimate each firm's Betas (βs) on daily market excess return, size, value, and momentum factor returns. We then calculate each firm's annual abnormal return, i.e., the Fama-French-adjusted return which is the excess return of the stock minus its Betas times the annual factor returns. We obtain Fama-French four factor returns and the risk-free rates from Kenneth French's database.

2.2 Empirical Methodology

We first assess whether individuals could gain excess returns by holding stocks in female-led firms relative to holding stocks in male-led firms. Therefore, we consider the following time-series specification (Wolfers, 2006):

$$Portfolio\ Excess\ Return_t = \alpha + \beta_1^*\left(Market_t - R_t^f\right) + \beta_2^* SMB_t + \beta_3^* HML_t + \beta_4^* UMD_t + \varepsilon_t \tag{1}$$

where the dependent variable is the daily excess return of a zero-investment portfolio (i.e., long male-headed firms and short female-headed firms). Market Excess Return is measured as return of the CRSP-weighted index minus the Treasury-Bill rate, SMB (Small Minus Big) is the Size factor, HML (High Minus Low) is the Value factor and UMD (Up minus Down) is the Momentum factor. The ε represents the disturbance term.

We also consider the following cross-sectional specification (Fama & MacBeth, 1973):

$$Mean\ Daily\ Excess\ Return_i = \alpha_0 + \alpha_1 CEO\_Gender_i + \gamma_1\beta_{i,1}^* + \gamma_2\beta_{i,2}^* + \gamma_3\beta_{i,3}^* + \gamma_4\beta_{i,4}^* + \varepsilon_i \tag{2}$$

which regresses the mean daily excess return of firm i on that firm's estimated Betas (βs) and CEO gender, a dummy variable assuming value equal to 1 when the CEO is male and zero otherwise.

Beyond expected returns, we also examine the effect of CEO gender on firm's abnormal returns as well as on the operating performance of female-led firms relative to male-led firms. The specification of this model is:

$$Performance_i = \beta_0 + \beta_1 CEO\_Gender_i + \beta_2 FirmControls_i + \beta_3 IndustryFE_i + \varepsilon_i \tag{3}$$

where the dependent variable corresponds respectively to the firm's yearly abnormal stock returns or to the firm's accounting performance, measured either by the return on assets (ROA) or by the Gross Profit Margin (GPM), or lastly by the Growth of Sales (GSA). The unit of observation is firm i during the year t, where year t is either 2020 or 2021. In terms of firm-specific characteristics, for abnormal stock returns, we control for Profitability, Return on Assets (ROE), Leverage, Cash Ratio, Size and Advertising of firm i. For operating performance, we control for Profitability, Leverage, Cash Ratio, Size and Advertising. We run regression specifications with industry fixed effects.

As a final robustness test to our results, we employ the specification by Kolev (2012). The corresponding model is as follows:

$$r_{it} = \alpha + \delta CEO_{Gender\,it} + \beta_1 (Market_t - R_t^f) + \beta_2 CEO\_Gender_{it} * (Market_t - R_t^f) + \zeta_1 SMB_t + \zeta_2 CEO\_Gender_{it} * SMB_t + \eta_1 HML_t + \eta_2 CEO\_Gender_{it} * HML_t + \tau_1 UMD_t + \tau_2 CEO\_Gender_{it} * UMD_t + \varepsilon_{it} \tag{4}$$

where the r_{it} is the net return on firm i in period t (day). Relevant regressors are described and denoted as in Models (1) to (3).

3. Analysis of Results

In this section we present and analyse our empirical findings. Table 2 presents results based on Model (1), for the years 2020 (Panel A) and 2021 (Panel B). We examine whether holding the portfolio of female-led firms yields higher $alpha$ (or α) than holding the portfolio of male-led firms. The portfolio maintains zero investment by employing the strategy of investing in the male portfolio and selling off the female portfolio. These strategies yield daily returns that are then regressed on standard factor return series. A significant α of this zero-investment portfolio conditional on risk factors will signal whether CEO gender has an influence on firm stock return. We present the results of the zero-investment portfolio in Col. 3 accompanied by the portfolio of male-headed firms and the portfolio of female-headed firms in Col. 1 and Col. 2, respectively. Despite the low R-square in Col. 3 of Panel A, attributed to the striking similarity in year 2020 between portfolios of male- and female-headed firms in their exposure to the risk factors (i.e., their βs), the time series regression of the zero-investment portfolio identifies insignificant difference between the alphas of the two portfolios (female outperformance 0.0045% daily). Hence, these results provide support for the insignificant effect of the CEO gender on stock returns. In Panel B, the 2021 evidence consistently supports the insignificant effect of the CEO gender, although the zero-investment portfolio is somewhat exposed to the size and value factors.

Table 2: Time-series regressions of daily returns (%) in zero-investment portfolio (long male-headed firms; short female-headed firms)

Panel A	(1) Portfolio of male-headed firms Jan-Dec, 2020	(2) Portfolio of female-headed firms Jan-Dec, 2020	(3) Zero-Investment Portfolio Jan-Dec, 2020
Alpha	0.034194*	0.03868	-0.004482
	(0.019782)	(0.02998)	(0.021299)
Market-Rf	1.03188***	1.03724***	-0.005359
(VWRF)	(0.009633)	(0.0146)	(0.010372)
Size	0.646344***	0.63937***	0.006969
(SMB)	(0.022808)	(0.03456)	(0.024557)
Value	0.468773***	0.45725***	0.011524
(HML)	(0.025511)	(0.03866)	(0.027468)
Momentum	-0.066409***	-0.08663***	0.020225
(UMD)	(0.019089)	(0.02893)	(0.020553)
Sample size	253	253	253
Adj R-sq	0.988	0.9731	0.0081
Panel B	**(1) Portfolio of male-headed firms Jan-Dec, 2021**	**(2) Portfolio of female-headed firms Jan-Dec, 2021**	**(3) Zero-Investment Portfolio Jan-Dec, 2021**
Alpha	-0.009336	0.02584	-0.03518
	(0.015859)	(0.02616)	(0.02779)
Market-Rf	1.106132***	1.07078***	0.03535
(VWRF)	(0.021581)	(0.03559)	(0.03781)
Size	0.572316***	0.46198***	0.11033***
(SMB)	(0.021708)	(0.0358)	(0.03803)
Value	0.412217***	0.30008***	0.11213***
(HML)	(0.014501)	(0.02392)	(0.02541)
Momentum	-0.092049*	-0.11347***	0.02143
(UMD)	(0.018834)	(0.03106)	(0.033)
Sample size	252	252	252
Adj R-sq	0.9592	0.8739	0.1196

Note: Market return is measured as an excess return of CRSP-weighted index minus the one-tenth Treasury rate. Size, Value, Momentum are factor returns extracted from Kenneth French's website. Standard errors in parentheses. Statistical Significance: *p<10%; **p<5%; ***p<1%.

In Table 3, based on Model (2), we report regressions in the cross-section for the firms' mean daily excess returns on firms' betas for a given year. The betas of firm i are estimated from daily returns of the same year. The coefficient of the CEO_Gender in Table 3 is statistically insignificant to explain the cross-sectional variation in mean daily returns during the pandemic. It must be noted, that in terms of the other coefficients, by looking at the 2020 returns (Col. 1), we observe a significantly positive market risk premium, while for 2021 a significantly negative market risk premium (-45.67%). The positive and negative signs of the market risk premia in the two years are robust to regressions using either the betas estimated in daily or in weekly frequency (not reported). While the actual market risk premium in 2021 is positive, the negative value we estimate implies an empirical rejection of the Fama-French model in 2021.

Table 3: Cross-sectional regressions of firm mean daily excess returns on firm betas

	(1) 2020 mean returns (on 2020 Betas)	(2) 2021 mean returns (on 2021 Betas)
Alpha	-0.03879 (0.06579)	0.65372*** (0.06329)
CEO_Gender	-0.03281 (0.05050)	-0.01089 (0.05327)
Beta-Market (VWRF)	0.36221*** (0.04666)	-0.45665*** (0.03262)
Beta-Size (SMB)	0.12323*** (0.01763)	0.18343*** (0.02093)
Beta-Value (HML)	-0.21760*** (0.02163)	0.28383*** (0.02611)
Beta-Momentum (UMD)	0.34763*** (0.02748)	0.68206*** (0.05169)
Sample size	1314	1451
Adj R-sq	0.1726	0.2905

Note: The dependent variable is the mean daily excess returns. CEO_gender is a dummy variable that assumes the value of 1 when the CEO is a male and 0 otherwise. The cross-sectional regressions of firms' mean daily excess returns on firm betas generate coefficients representing daily risk premiums. For presentational purposes, the coefficients are then multiplied by 252 for conversion into yearly risk premia. Standard errors in parentheses. Statistical significance: *p<10%; **p<5%; ***p<1%.

Overall, when the four-factor model adequately accounts for the cross-sectional variations in mean returns, the estimated (market, size, value, and momentum) risk premia should be quite close to the actual. That is not the case in our Table 3, particularly for the year 2021. Nevertheless, the Fama-French model focuses on explaining variations in long-term expected returns rather than variations in short-term mean returns (Roll & Ross, 1994; Blitz & Hanauer, 2023). It should be of no surprise that the multifactor model fails for a duration as short as one year. Yet, since the betas are correctly estimated, the outcomes in Table 3 are still valid for identifying insignificant effects of CEO gender on firm return in 2020 and 2021.

The output of Table 4 is based on Model (3) and shows results of regressing yearly Fama-French-adjusted (abnormal) returns on firms' CEO_gender and other firm characteristics. Col. (1) and (2) refer to the year 2020 and Col. (3) and (4) refer to the year 2021. Col. (1) and (3) use CEO_gender as the only independent variable, while in Col. (2) and (4) we add firm controls as independent variables. All specifications include industry fixed effects. Standard errors are robust to heteroscedasticity. According to our results, the gender of the CEO is not significant to explain abnormal stock returns, and this continues to be the case after including firm controls.

Table 4: Cross-sectional regressions of yearly 2020-2021 Abnormal Returns (%)

	(1) Abnormal Returns 2020	(2) Abnormal Returns 2020	(3) Abnormal Returns 2021	(4) Abnormal Returns 2021
CEO_gender	0.211 (5.675)	-1.223 (6.510)	3.495 (6.619)	1.4666 (8.0895)
Profitability		14.213*** (4.730)		-0.1512 (3.5207)
ROE		-0.035 (1.090)		1.7670 (2.9525)
Leverage		38.017*** (8.795)		-21.5571* (12.6474)
Cash Ratio		-1.295*** (0.465))		-1.3610 (1.2020)
Size		-11.201*** (2.605)		-4,1673 (3.2352)
Advertising		21.474 (40.612)		-48.0324 (62.4336)
Constant	27.492*** (10.550)	27.383 (16.995)	28.432*** (9.708)	52.0550*** (15.9752)
Industry FE	Yes	Yes	Yes	Yes
Obs.	1314	1037	1357	1089
Adj R-square	0.068	0.081	0.04329	0.03445
Residual Std. Error	47.728 (df = 1304)	49.19 (df = 1021)	59.59 (df = 1331)	65.02 (df = 1058)
F-Stat	11.657*** (df = 9; 1304)	7.09*** (df = 15; 1021)	3.454*** (df = 25; 1331)	2.294*** (df = 30; 1058)

Note: Data is from COMPUSTAT (CAPITAL IQ) and EXECUCOMP databases. We use OLS regressions. The dependent variable is the yearly abnormal returns. CEO_gender is a dummy variable that assumes the value of 1 when the CEO is a male and 0 otherwise. Control characteristics include Profitability, ROE, Leverage, Cash Ratio, Size and Advertising. We control for industry fixed effects. Standard errors in parentheses. Statistical Significance: *p<10%; **p<5%; ***p<1%.

Next, we examine if the CEO's gender is effective to explain the firm's operating performance. Our cross-sectional regressions are presented in Table 5 and are based on Model (3). Operating performance is measured by ROA in Col. (1) and (2), by the Gross Profit Margin (GPM) in Col. (3) and (4) and by the Growth of Sales (GSA) in Col. (5) and (6). Holding all other variables constant, operating performance does not increase significantly if the company is led by a female CEO as opposed to a male CEO, according to the insignificant coefficient of CEO_Gender in all specifications. These results contradict with the findings by Khan and Vieito (2013), according to which female CEOs impact positively firm performance. However, in the paper of Khan and Vieito (2013) a Size component is included, specified using principal component analysis and is a function of three factors (Assets, Sales, and Firm Market Value).

Table 5: Cross-sectional regressions of accounting performance

	(1) ROA 2020	(2) ROA 2021	(3) GPM 2020	(4) GPM 2021	(5) GSA 2020	(6) GSA 2021
CEO_gender	-0.004806 (0.01036)	-0.0068043 (0.0121049)	0.041486 (0.028501)	0.013653 (0.037099)	0.013214 (0.033426)	0.10122 (0.12257)
Profitability	0.1778*** (0.007315)	0.064875*** (0.0052818)	0.912689*** (0.020118)	0.489678*** (0.016318)	0.041006* (0.023594)	0.02024 (0.04791)
Debt-to-Asset	0.03632*** (0.01012)	0.041127*** (0.01462)	0.028861 (0.027820)	0.032445 (0.044911)	-0.091588*** (0.032628)	-0.16855 (0.13771)
Cash ratio	0.001917** (0.0007468)	0.0019171 (0.001828)	0.002434 (0.002054)	-0.002221 (0.005602)	0.005600** (0.002409)	-0.02833 (0.01750)
Size	0.01231*** (0.003897)	0.025593*** (0.0046943)	-0.084487*** (0.010717)	-0.029786** (0.014386)	-0.048333*** (0.012569)	-0.11197** (0.04502)
Advertising	0.08868 (0.06441)	-0.1360997 (0.0935359)	1.701436*** (0.177159)	1.455337*** (0.287357)	-0.070557 (0.207774)	-0.21490 (0.87933)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1092	1135	1092	1135	1080	997
Adj R-square	0.4361	0.2032	0.6922	0.4842	0.0801	0.0316

Note: Data is from COMPUSTAT CAPITAL IQ and EXECUCOMP databases. OLS regressions. The dependent variable ROA is the Net Income before Extraordinary and Discontinued Items. The dependent variable GPM is the Gross Profit Margin, defined as the Gross Profit per Sales. The dependent variable GSA is the Growth of Sales, where Sales (scaled in millions) is defined as gross sales reduced by cash discounts, trade discounts, returned sales, excise taxes, and value-added taxes and allowances for which credit is given to customers. CEO_Gender is a dummy variable that assumes the value of 1 when the CEO is a male and 0 otherwise. We control for industry fixed effects. Standard errors in parentheses. Statistical Significance: *p<10%; **p<5%; ***p<1%.

As an additional robustness check, we use Kolev's (2012) approach. The panel regressions are presented in Table 6 and are based on Model (4). The differential return seems to be insignificant, as reported by the coefficient on CEO_Gender, although female CEOs outperform male CEOs in both years. In Model (4), β_1 measures the market risk of female-led firms, and $(\beta_1 + \beta_2)$ measures the market risk of male-headed firms. The same is true for other risk factors. In Col. (2) and (4), female- and male-led firms' exposure to each risk factor is almost identical to Table 2, a result not surprising given the linear nature of the regressions. Nevertheless, Table 6 accounts for information of individual firms unavailable when returns are averaged across firms, which is the case in Table 2, hence the non-identical standard errors in Tables 2 and 6. The cluster-robust standard errors in Table 6 turn out to be not significantly different from the standard errors in Table 2, suggesting that our findings from Table 2 are reinforced by the findings from Table 6. It becomes evident that Wolfers' (2006) and Kolev's (2012) methodologies produce contrasting findings in long-term data but consistent findings in the short-term period we examine.

Table 6: Panel regressions of daily Stock Returns (%)

	2020		2021	
	(1)	(2)	(3)	(4)
CEO_Gender	-0.0066 (0.0203)	-0.0044 (0.0198)	-0.0296 (0.0291)	-0.0352 (0.0270)
MktRf	1.1718*** (0.0446)	1.0374*** (0.0267)	1.0747*** (0.0465)	1.0708*** (0.0346)
CEO_Gender*MktRf	-0.0058 (0.0151)	-0.0055 (0.0156)	0.0582* (0.0327)	0.0353 (0.0395)
SMB		0.6388*** (0.0416)		0.4620*** (0.0374)
CEO_Gender*SMB		0.0075 (0.0475)		0.1105*** (0.0417)
HML		0.4568*** (0.0470)		0.3001*** (0.0271)
CEO_Gender*HML		0.0120 (0.0298)		0.1122*** (0.0275)
UMD		-0.0871*** (0.0289)		-0.1135*** (0.0330)
CEO_Gender*UMD		0.0206 (0.0214)		0.0214 (0.0356)
Sample size	385184	385184	394666	394666

Note: Cluster-robust standard errors in parentheses. The numbers of clusters (days) are 253 and 252. Statistical Significance: *p<10%; **p<5%; ***p<1%.

4. Conclusion

The impact of COVID-19 on the U.S. stock market was historically unprecedented. Based on a panel of US firms during the pandemic period of 2020-2021, we examine whether firms led by female CEOs exhibited comparable performance relative to firms led by male CEOs. According to our results, during the coronavirus pandemic, firms led by female CEOs are not associated with greater performance than businesses led by male CEOs. Our findings are robust in terms of stock market performance and operating performance.

It is worth mentioning that differences in firm performance between female and male-headed firms may be attributed to the disparity in risk attitudes between female and male CEOs, particularly during the highly disruptive period of the COVID-19 pandemic. The empirical evidence is inconclusive regarding the discrepancy in risk preferences between female and male executives. Some papers support the notion that female executives exhibit more risk aversion than male executives (Barua et al., 2010; Huang and Kisgen, 2013; Liu et al., 2016). Other papers suggest that females and males at top management positions are either similar in terms of risk preferences (Atkinson et al., 2003), or more generally, that there is no support that female executives are more risk-averse than their male counterparts (Doan and Iskandar-Datta, 2020). Given that we do not find substantial variation in performance between female and male-headed firms, the focus now is transferred to how the introduction of a highly disruptive period would affect the risk attitudes between female and male executives. This question is left for future research.

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DRIVERS OF PROFIT CONVERGENCE IN EURO AREA BANKS

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Abstract
Since there are persistent concerns about the viability of euro area banks, we analyse their profit recovery in the post-crisis period, applying the concepts of β and σ convergence as well as the Phillips and Sul clustering algorithm. The results are consistent with ROE convergence, but to different levels across bank groups. The clustering analysis reveals the existence of banks with solid performance, but also a group of persistent underperformers. We find that non-interest income and operational efficiency emerge as crucial discriminating factors to explain the banks' relative post-crisis ROE dynamics. Supervisors and bank managers are advised to monitor and reinforce bank business model viability.

Keywords: Euro Area banks; Bank profitability; β convergence; σ convergence; Club clustering analysis

1. Introduction

The Great Financial crisis (GFC) of 2008 and the subsequent European sovereign debt crisis caused substantial divergence in the profitability of euro area banks. While some banks were able to absorb the negative shocks, others were hit hard by non-performing loans and valuation losses on their assets. The question we address is whether or not the vulnerable banks have been able to recover and what the drivers of profit convergence are. This is of crucial importance for the euro area economy, since banks provide the bulk of the financing of corporations as well as households. Moreover, there is evidence that the weaknesses of the business model of vulnerable banks causes them to perform badly whenever a new crisis occurs (Fahlenbrach et al., 2012). In that respect, the persistent low market/book equity ratios exhibited by a substantial number of euro area banks is a signal that investors doubt the viability of the banks' business model. In the same vein, Altavilla et al. (2021) show that the average return on equity (ROE) of euro area banks has remained below their cost of equity (COE) for the entire post-GFC period. As a result, the Supervisory Board of the European Central Bank has voiced concerns about the long-term profit potential of the banks (Enria, 2023). To assess the banks' longer-term profit potential, we investigate the post-crisis convergence of bank profitability and the underlying drivers.

Several papers have researched convergence in European banking, but the focus is mostly on operational efficiency of banks (Casu & Girardone, 2010; Degl'Innocenti et al., 2017; Matousek et al., 2015). In terms of overall profitability, we expect convergence because euro area banks operate in an environment characterised by similar regulations (e.g. Basel III), supervision (by the ECB) and monetary policy conditions (Altavilla et al., 2018; Loipersberger, 2018). This may induce similar behaviour by the banks. Nevertheless, we also hypothesise that performance of some banks may diverge resulting from negative shocks combined with unfavourable initial conditions (e.g. legacy bad loans) or a deficient risk culture (Fahlenbrach et al., 2012). Lamers et al. (2022) report that euro area banks' ROE recovered in the period between the GFC and the covid pandemic, but do not address the underlying drivers. We extend this analysis by focusing on the building blocks of bank ROE, such as the net interest margin, income diversification, cost efficiency and asset quality. In terms of empirical design, we use the Phillips and Sul (PS) clustering approach, as in Matousek et al. (2015), but we apply it to the underlying drivers of bank profits.

2. Data and Methodology

2.1 Data

Since we focus on profit convergence following the GFC and sovereign crisis, the period under investigation is 2013-2021. The PS clustering algorithm requires banks to be present in the sample over the entire period. Therefore, we use a balanced sample of 80 euro area banks under ECB supervision. Overall bank profitability is captured by ROE[1], but we also analyse the underlying components, i.e. the net interest margin (NIM), non-interest income (NONINT/total income), cost efficiency (cost/income-ratio, C/I) and non-performing loans (NPL/Loans) (Davis et al., 2022; Mergaerts and Vander Vennet, 2016). The data is retrieved from S&P Capital IQ Pro, and Table 1 presents the summary statistics for the profit variables as well as other relevant bank characteristics.

Table 1: Summary statistics (winsorised data: 5%-95%)

	n	mean	median	min	max	sd
Size (=log(TA))	825	18.15	18.07	12.94	21.69	1.59
ROA	816	0.44	0.44	-1.63	1.65	0.68
ROE	816	6.04	7.28	-24.78	21.11	9
NIM	782	1.4	1.34	0.35	2.74	0.64
NONINT/TI	813	37.7	38.93	-0.5	74.27	18.23
C/I	813	62.31	61.57	40.34	87.29	12.87
NPL/Loans	792	6.1	3.06	0.43	30.22	7.83
CET1/RWA	793	16.42	14.94	6.63	29.43	5.17
RWA/TA	806	39.56	36.57	14.25	75.48	16.35
Loans/TA	812	58.98	60.84	23.38	82.47	15.86
Deposits/TA	703	67.61	73.03	30.63	88.34	17.16

[1] ROE is computed as net income before tax divided by total equity; we use before tax profit since tax regimes are different depending on the country in which a bank is headquartered.

2.2 Methodology

2.2.1 Beta and Sigma Convergence

To investigate convergence of bank performance, we use the concepts of β and σ convergence, introduced by Barro and Sala-I-Martin (1992). The initial purpose of these concepts was to investigate the presence of convergence between rich and poor countries in terms of GDP per capita. In the context of bank performance, β convergence would imply that banks with an initially lower performance realise a higher ROE growth rate compared to banks that already perform better. The σ convergence would then indicate a lower dispersion in bank performance across euro area banks. Similar to Lamers et al. (2022), we estimate the following equations:

$$\Delta PERF_{i,t}=\alpha_p+ \beta \, PERF_{i,\, t\text{-}1}+ \varepsilon_{i,t} \tag{1}$$

$$\Delta W_{i,t}= \alpha_w+ \sigma \, W_{i,t\text{-}1}+\mu_{i,t} \tag{2}$$

The variable $PERF_{i,\,t}$ refers to the performance (ROE and the underlying components) of bank i at time t. The dependent variable in equation (1) is the difference of $PERF_i$ between time t and time t-1. To analyse σ convergence we need $W_{i,t}= PERF_{i,t}-\overline{PERF_t}$, with $\overline{PERF_t}$ the average of the profitability of all banks at time t. The dependent variable in equation (2) is the difference in $W_{i,t}$ between time t and time t-1.

The presence of β (σ) convergence is confirmed if the β- (σ-) coefficient is negative and significant. β convergence is a necessary but not a sufficient condition for σ convergence to occur (Weill, 2009).

2.2.2 Phillips and Sul Clustering Algorithm

To analyse groups of banks with different profit dynamics, we use the model introduced by Phillips and Sul (2007, 2009) because it dynamically establishes convergence clusters, the model eliminates the need for assumptions about stationarity, and offers the possibility of different transitional paths (Sichera & Pizzuto, 2019). This method is a non-linear time-varying factor model with both common and individual specific components (Phillips & Sul, 2007). According to Phillips and Sul (2007), if we find clusters of banks with varying profit dynamics, we can uncover the drivers of these different paths based on the characteristics of the banks.

In our econometric analysis, we use the package ConvergenceClubs in R, introduced by Sichera and Pizzuto (2019). The first step in this algorithm is to perform a log-t regression test for convergence on the whole sample. When the null hypothesis of convergence is rejected, there is either no convergence or there are clusters of convergence. To know which hypothesis prevails, the test should be performed again on subgroups. The formula of this log-t regression test is as follows:

$$\log\frac{H_1}{H_t}-2\log L(t) = a + b\,\log t + u_t \tag{3}$$

$$\text{with} \qquad H_t= \frac{1}{N}\sum_{i=1}^{N} (h_{i,t}-1)^2 \;;\; h_{it}= \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} \tag{4}$$

In this analysis $L(t) = \log(t)$, as this is preferred over the other possibilities[2] in terms of asymptotic power and is thus the recommended L(t)-function in practice (Phillips & Sul, 2007). The term $h_{i,t}$ maps the transition path of an entity i (in our case this entity is a bank) relative to the average level.

Based on these formulae a (robust conventional) test statistic for the coefficient b must be computed[3] . For the null hypothesis to hold, b must be greater than or equal to 0. If the hypothesis gets rejected, the next step consists in finding subgroups with convergence. One of the benefits of the PS algorithm is that it provides a method to identify those subgroups, based on the data. The clusters are determined based on a repetition of the log-t regression test (Phillips & Sul, 2007).

The step-by-step procedure proposed by Phillips and Sul is as follows: (1) Order the entities based on their last observation; (2) Form a core group; (3) Add entities to the core group if they meet the condition (t > c* (a chosen critical value[4])); (4) Apply the stopping rule. The stopping rule consists of taking all the entities that did not meet the t>c* criteria together and test whether they form a cluster. If they do form a cluster, there are a total of two clubs and the procedure can be stopped; if it gets rejected by the log-t test, the step-by-step procedure is repeated on this subsample. Finally, to avoid overidentifying clusters a merging algorithm has to be applied to test whether some subsamples can be merged without rejecting the convergence hypothesis.

3. Results

3.1 β and σ convergence

Table 2 reveals negative β and σ coefficients for the whole sample, indicating convergence in terms of ROE towards a long-term level of 6.9%. The question is whether this is a general convergence or whether there are subgroups of banks that converge to different ROE levels. Therefore, we rank the banks from high to low ROE in 2013 and perform the analysis on the highest and lowest quartile. As shown in Table 2, the coefficients of these subgroups also indicate the presence of convergence. However, their estimated long-term convergence levels differ considerably (12.1% for the high performers versus 1.9% for the group of banks with low initial ROE) from the one obtained for the entire sample (6.9%). This suggests the presence of clusters of convergence with different profit paths. In order to uncover the dynamics of profitability across groups, and especially the underlying drivers, we apply the PS clustering algorithm as it does not rely on predetermined groups but lets the data yield the relevant clusters.

[2] $L(t) = log(log(t))$ or $L(t) = log(log(log(t)))$

[3] All details about the exact calculation and further explanation can be found in Phillips and Sul (2007, 2009).

[4] The higher the critical value, the higher the conservativeness meaning that banks have a lower probability to be assigned to the same cluster. For a large timespan (T>50) Phillips and Sul (2009) suggest -1.65 as critical value, for a smaller time span a bigger critical value is justified, Phillips and Sul (2009) then suggest 0.

Table 2: β and σ convergence ROE (pooled OLS[5]; 2013-2021)

	Beta convergence			Sigma convergence		
	Dependent variable:			*Dependent variable:*		
	ΔROE_t			$\Delta W_{ROE,t}$		
	Whole sample	Banks with high initial ROE	Banks with low initial ROE	Whole sample	Banks with high initial ROE	Banks with low initial ROE
	(1)	(2)	(3)	(4)	(5)	(6)
ROE_{t-1}	-0.473***	-0.334***	-0.605***			
	(-0.033)	(-0.101)	(-0.054)			
$W_{ROE,t-1}$				-0.466***	-0.273***	-0.641***
				(-0.037)	(-0.076)	(-0.059)
Constant	3.242***	-0.334***	1.154	-0.016	1.111*	-0.138*
	(-0.292)	(-0.101)	(-0.746)	(-0.302)	(-0.623)	(-0.074)
LT conv. Level	6.854	12.147	1.907	/	/	/
Observations	717	179	179	717	179	179
R^2	0.28	0.186	0.353	0.274	0.152	0.364
Adjusted R^2	0.279	0.181	0.349	0.273	0.147	0.361
F Statistic	278.114***	40.414***	96.473***	269.232***	31.793***	101.456***
	(df = 1; 715)	(df = 1; 177)	(df = 1; 177)	(df = 1; 715)	(df = 1; 177)	(df = 1; 177)

Note: *p<0.1; **p<0.05; ***p<0.01 s.e. clustered at bank level.

3.2 Phillips and Sul Clustering Algorithm

By applying the clustering algorithm on the banks' ROE with a low c* value (c*=7), two clusters of convergence are found. Figure 1a, shows their average transition paths, relative to the sample average[6]. However, the first group contains the majority of the banks (73 of the 80 banks), hence it is too coarse. To obtain a more granular clustering, we apply a sequential clustering using higher c*'s (see footnote 4). The underperformers are retrieved from the initial run (club2 Figure 1a), while the outperformers are obtained from the clustering shown in Figure 1b (club1).

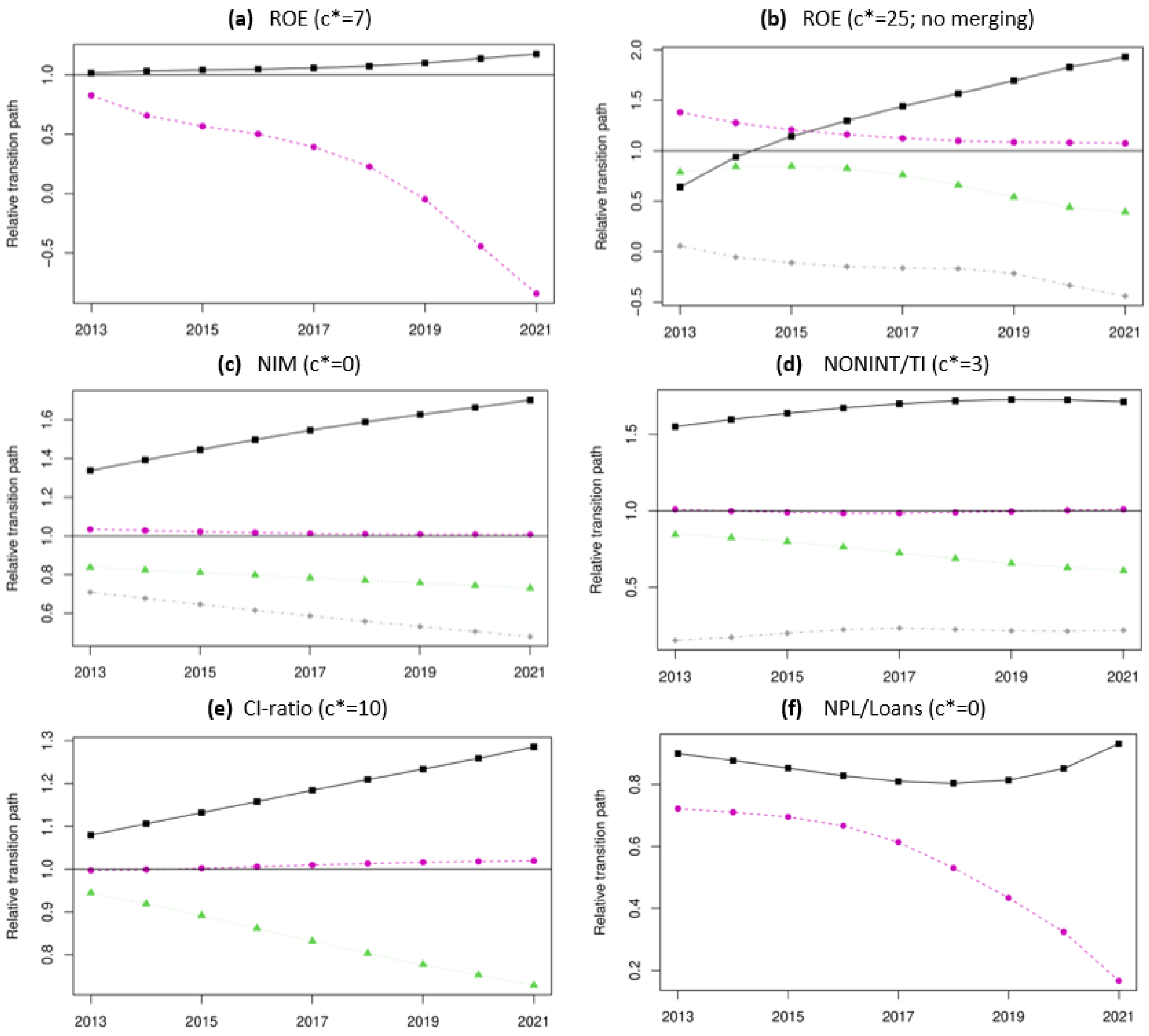
To uncover the behaviour of the underlying drivers of ROE, we apply the PS clustering to NIM, NONINT, C/I and NPL, yielding relative transition paths as depicted in Figure 1c/d/e/f. Clubs close to the

[5] Other estimations (FE, two-ways FE and RE) were also applied and they confirm the convergence result.

[6] The sample average is presented in the figures as a horizontal line at the unit level 1, with lines positioned above indicating superior performance compared to the average, while lines below indicate inferior performance.

sample average are deemed average performers, while those above (below) the neutral line are classified as outperformers (underperformers).

Figure 1: **Average transition path clubs based on mentioned clustering variable**



Note: club1: square, club2: dot, club3: triangle, club4: rhombus; **(f)** divergent units (5 banks) not in figure.

Having identified distinct performance groups through clustering, we analyse their associated bank characteristics to gain deeper insights into the dynamics behind these performance paths. On the diagonal of Table 3, we present the (statistically significant) differences between outperformers and underperformers for the variables of interest (ROE, NIM, NONINT, C/I and NPL) resulting from the club clustering analysis. Investigating the associated bank characteristics allows to identify the main drivers of bank profitability and how profits are related to the banks' risk profile.

Table 3: Overview average key summary statistics for each clustering result

Clustering variable			Average of bank characteristics								
			ROE	NIM	NONINT /TI	C/I-ratio	NPL /Loans	RWA /TA	CET1 /RWA	Loans /TA	Deposits /TA
(1)	ROE	Outperformers	8.73***	1.70	38.32***	58.92***	6.86***	42.48**	16.28	61.71	71.72**
		Underperformers	0.83***	1.63	31.01***	67.62***	13.76***	47.98**	16.97	60.24	64.60**
(2)	NIM	Outperformers	2.34***	2.12***	29.97***	60.00***	13.77***	54.61***	16.48	65.55***	75.74***
		Underperformers	6.85***	0.94***	48.78***	65.88***	3.71***	33.54***	15.75	50.12***	60.94***
(3)	NONINT /TI	Outperformers	8.65**	0.91***	63.02***	64.91***	3.20***	29.92***	16.33**	44.33***	57.19***
		Underperformers	4.93**	1.54***	19.74***	59.62***	7.59***	37.46***	18.00**	67.49***	67.57***
(4)	C/I-ratio	Outperformers	8.07***	1.49	30.06***	52.22***	4.74***	37.95	19.3***	65.54***	65.87
		Underperformers	1.42***	1.40	40.28***	74.09***	8.41***	39.70	15.11***	53.63***	65.71
(5)	NPL /Loans	Outperformers	6.51***	1.17***	39.95***	61.17	3.90***	32.68***	19.41***	60.26**	68.56***
		Underperformers	-4.94***	2.37***	21.82***	58.50	26.47***	57.70***	15.32***	65.68**	82.58***

Note: t-tests were performed to test whether there is a significant difference between the outperformers and underperformers. *, ** and *** indicate significance at 10%, 5% and 1% respectively.

The first row of Table 3 demonstrates that the clustering algorithm effectively distinguishes the good from the bad performers (ROE of 8.7% versus 0.8%)[7]. From the ROE row we also observe that the NIM is not a discriminating contributor, with similar margins for out- and underperformers. This can be attributed to the compressed bank NIMs during the low-interest-rate period caused by the unconventional monetary policy actions by the ECB (Claessens et al., 2018; Present et al., 2023). The first row suggests that the main contributors to a higher ROE are NONINT, C/I and NPL. Hence, revenue diversification, operational efficiency and asset quality appear as the dominant drivers of ROE. Since these variables reflect business model choices, competent bank managers should be able to increase the structural profitability of their banks.

These findings are confirmed when combining the ROE column and the values of the underlying drivers in rows 2-5. The NIM outperformers achieve a NIM of 2.12% versus 0.94% for the underperformers, but this is not translated in a superior ROE. In contrast, a higher NONINT (63% for the diversified banks versus 19.7% for the retail banks), a lower C/I (52.2% for the most efficient banks versus 74.1% for the underperformers) and lower NPL (3.9% for the banks with good loan quality versus 26.5% for those with the highest proportion of bad loans) is reflected in a significantly higher ROE. We conclude that, under the period of investigation, NIM, which is influenced by financial markets rather than bank management, was not a driver of ROE outperformance, whereas diversification, cost efficiency and NPLs are, and these are key performance indicators for bank managers.

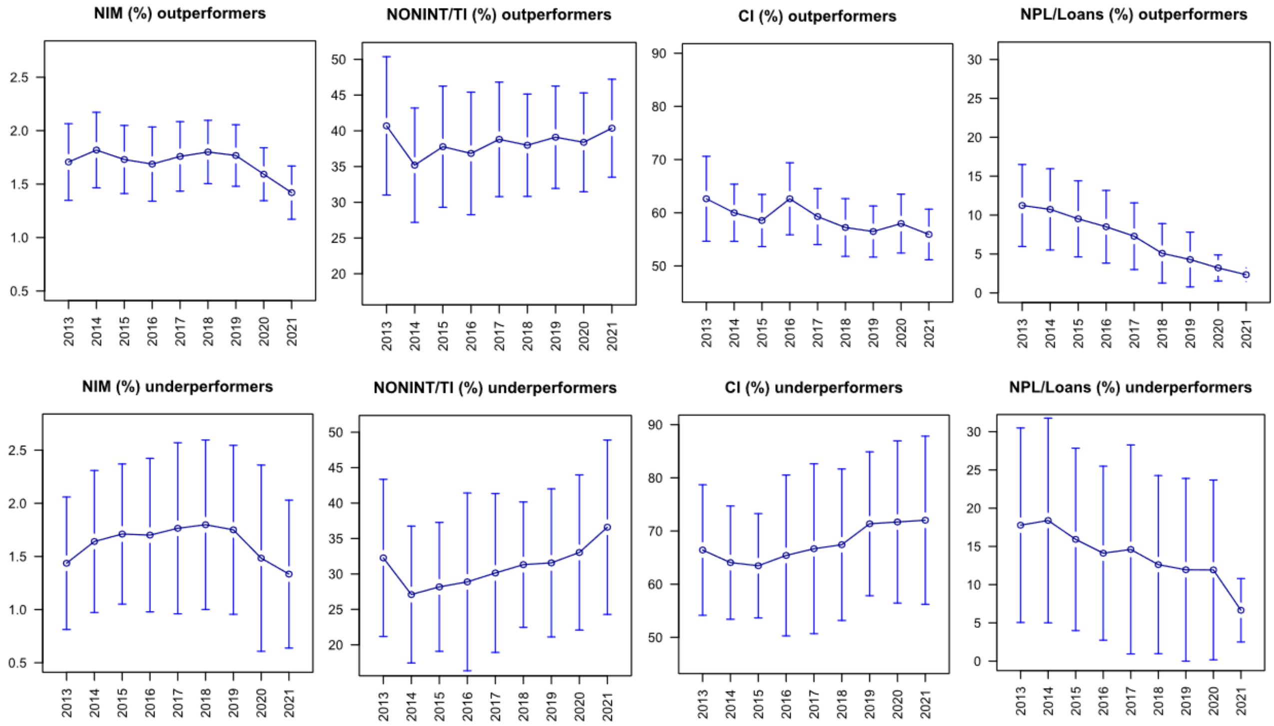
Finally, a higher ROE is not associated with more risk taking since CET1/RWA is not different for high and low-ROE banks, whereas RWA/TA is even lower for ROE outperformers. The balance sheet indicators loans/TA and deposits/TA exhibit the expected behaviour, e.g. high-NONINT diversified banks have significantly lower loans/TA and deposits/TA.

Besides averages it is important to look at temporal trends as well. Figure 2 shows declining NPLs and increasing non-interest income for underperforming banks, but a deteriorating cost-to-income ratio.

[7] The list of underperforming and outperforming banks in terms of ROE can be found in the Appendix. Both clusters contain banks headquartered in various countries, hence the clustering is not driven by the core periphery dichotomy.

Enhancing operational efficiency is thus imperative for their performance enhancement and long-term stability.

Figure 2: Evolution of bank characteristics for bank groups based on ROE clustering results



4. Conclusion

Our analysis reveals convergence of post-crisis performance of euro area banks, but we identify different clusters of ROE convergence, including a group of persistent underperformers. The clustering analysis of the underlying profit drivers uncovers that diversification of revenues on the income side and better cost efficiency and NPL management on the expenditure side are key to restore bank profitability. Bank supervisors, i.e. the ECB for euro area banks, should scrutinize the business model sustainability of the banks. If the bank cannot upgrade their performance through managerial actions, mergers and acquisitions, or even resolution in some cases, may be warranted to restructure the weak banks.

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OIL VOLATILITY-OF-VOLATILITY AND TAIL RISK OF COMMODITIES

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Abstract

We examine the information content of oil volatility-of-volatility (VOV), constructed from the past 1-month OVX (implied volatility in crude oil market), on the expected tail risk of commodities proxied by Value at Risk (VaR) and Expected Shortfall (ES). Specifically, we find oil VOV predicts 1-step-ahead tail risks of Energy and the Aggregate Commodity sector (GSCI) for both in-sample and out-of-sample. Our results indicate the important role of crude oil in overall commodity markets by incorporating forward-looking information of OVX. Our findings are robust and complement the strand of literature about the leading role of crude oil in commodity markets.

Keywords: Commodity markets, volatility-of-volatility risk, expected tail risk

1. Introduction

Over the past decade, commodity markets have experienced substantial fluctuations. The availability and popularity of new commodity-linked securities, due to the financialisation of the commodity markets, have led to extraordinary shifts in return dynamics of commodities. An emerging literature has focused on understanding tail risk in commodity markets. Value at Risk (VaR) and Expected Shortfall (ES) are two well-known metrics used to quantify tail risk. Specifically, VaR measures the potential maximum loss of an investment at a certain confidence level over a specific time frame. In contrast, ES takes an advantage of sub-addition by considering the expected value of the loss of the portfolio below a certain confidence level and is more sensitive to the shape of the tail of loss distribution (e.g., Frey and McNeil, 2002). Both VaR and ES have been widely used as measures for tail risks, which is essential for asset pricing and risk management.

Among commodities, the crude oil market plays a crucial role in transmitting risk among commodity markets, such as precious metal markets (e.g., Ahmed et al., 2022; Reboredo & Ugolini, 2016; Shahzad et al., 2019), clean energy sectors (Foglia et al., 2022), and financial sectors (Zhao et al., 2022). The literature has demonstrated that volatility-of-volatility (VOV) is a significant state variable containing nonredundant pricing information of oil volatility. In this paper, we contribute to this strand of research by providing evidence that VOV of oil market predicts tail risks of several other commodities, including energy and the aggregate commodity sector[1].

Crude oil price plays an important role in commodity markets since crude oil is a major input for production, and therefore, its prices are closely related to the costs of production and consumption. For example, Tyner (2010) finds that higher crude oil prices lead to higher gasoline prices, and subsequently higher demand for corn ethanol, which finally causes higher corn and commodity prices. Baumeister and Kilian (2014) also identify evidence of higher prices of agricultural commodities due to the transmission of oil price shocks. Melichar and Atems (2019) demonstrate that oil-demand shocks serve as the main driver for higher commodity prices before 2006, whereas oil supply shocks show impacts after expanded ethanol production since 2006. Higher oil prices are closely related to increasing volatility and uncertainty of volatility (i.e., VOV). Thus, oil VOV, a measure of the uncertainty of implied oil volatility, is likely to have a major impact on future commodity prices.

We mainly investigate the predictability of oil VOV on the future tail risk, proxied by VaR and ES, of the aggregate commodity market and its five subsectors, namely, energy, precious metal, industrial metal, agriculture, and livestock. Specifically, oil VOV shows significant predictability for the energy sector and the aggregate commodity market, using both tail risk measures of VaR and ES. These findings are consistent with previous studies that tail risk of oil market spillovers to other commodity markets such as metals and other energy sectors. Our results are robust after controlling for other volatility-related variables of equity and crude oil markets and fundamental economic variables. In addition, we perform out-of-sample tests by employing several statistics including out-of-sample R-square (R^2_{OS}), McCracken's (2007) F-statistic (MSE-F), and ENC statistic proposed by Clark and McCracken (2001) (ENC-NEW).

Our contributions are mainly two-folded. First, we identify an oil-market factor representing the uncertainty level of oil volatility that significantly improves the forecasting performance on the tail risk of commodity markets, whereas most previous literature has focused on the oil implied volatility and very limited discussions have so far been put forward about the role of oil VOV. Second, our results shed light on the linkage of tail risk between oil market and other commodities, by utilising the forward-looking information contained in oil VOV.

2. Data and key variables

2.1 Data

The empirical analysis covers the period of May 2007 to July 2021. We obtain all daily data from LSGE Datastream which includes volatility-related variables such as OVX, VIX, and VVIX and price variables from aggregate commodity market, precious metal sector, industrial metal sector, livestock sector, agriculture sector, and energy sector.

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[1] We proxy aggregate commodity market, energy, precious metal, industrial metal, agriculture, and livestock by using S&P GSCI Commodity, S&P GSCI Energy, S&P GSCI Precious Metal, S&P GSCI Industrial Metal, S&P GSCI Agriculture, and S&P GSCI Livestock, respectively.

2.2 Oil VOV

The oil VOV measure, denoted by vov_t^2, is computed based on the EWMA model as following:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)\mu_{t-1}^2, \tag{1}$$

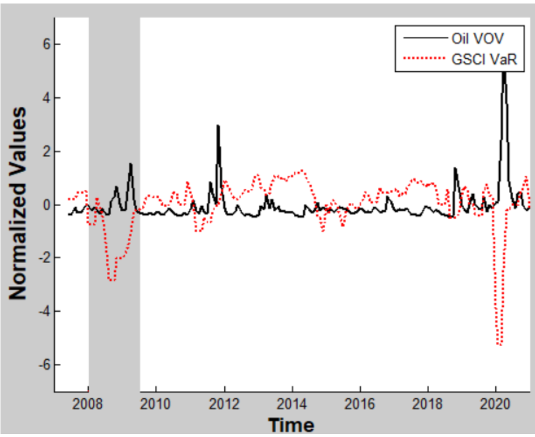
where μ_t is the logarithmic return of OVX, σ_t denotes the conditional volatility of the gross return of the OVX, and λ measures the degree of the weighting decrease, set with the value of 0.94.[2]

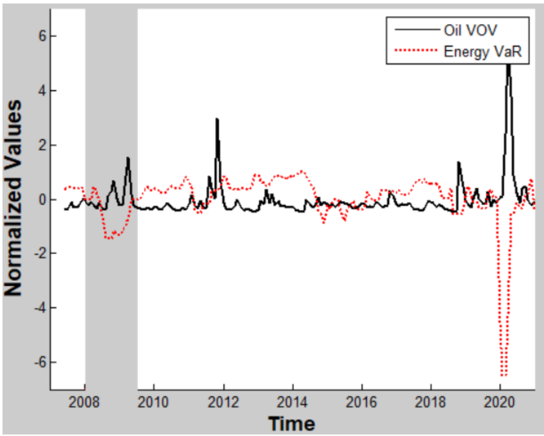
2.3 Tail risk measure

We consider the two most commonly used tail risk measures, namely Value-at-risk (VaR) and Expected Shortfall (ES), where the former measures the potential risk of loss, or the largest value of the potential loss, and the latter measures the expected portfolio return in the left tails. Both VaR and ES are computed at risk level of 5%, by using historic 3-month daily returns, namely, historical simulation (HS). Compared to other computation methods, this method is simpler and more straightforward (Christoffersen, 2003; Dowd, 2002; Kuester et al., 2006). The separate Appendix (Table A.1) presents the summary statistics for the key variables, namely, oil VOV, VaR, and ES at 5% level for the Aggregate commodity sector (GSCI), Energy, Precious Metals, Agriculture, and Livestock sector. Figure 1 shows the time-series plots of oil VOV and tail risk measure of each commodity sector with Panel A using VaR and Panel B using ES, respectively, which can provide clearer insights into how the variables interact with each other.

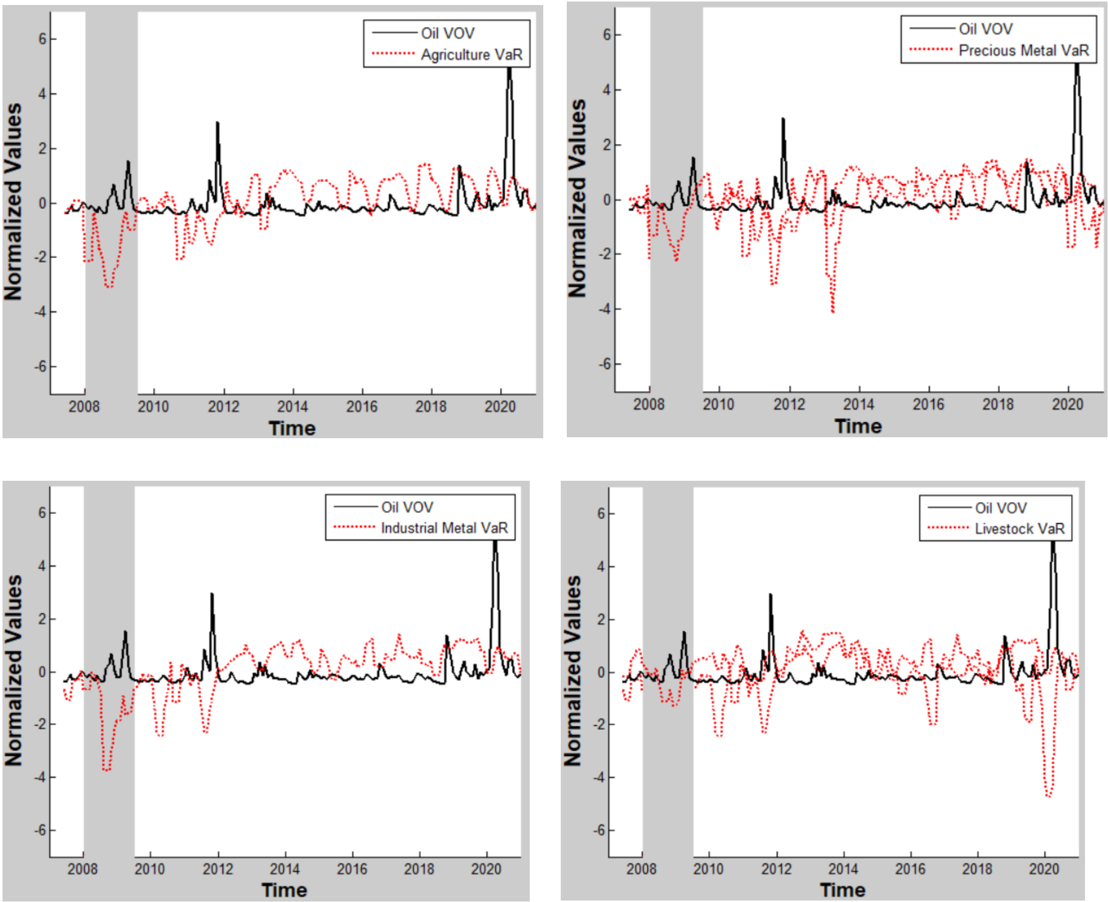
Figure 1: Oil VOV and Tail Risks of Commodities

Panel A. Tail Risks Proxied by VaR

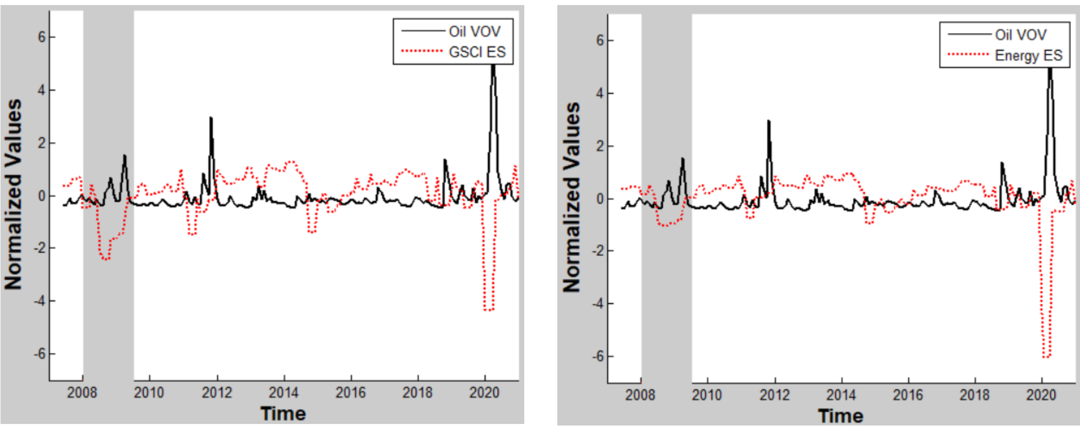


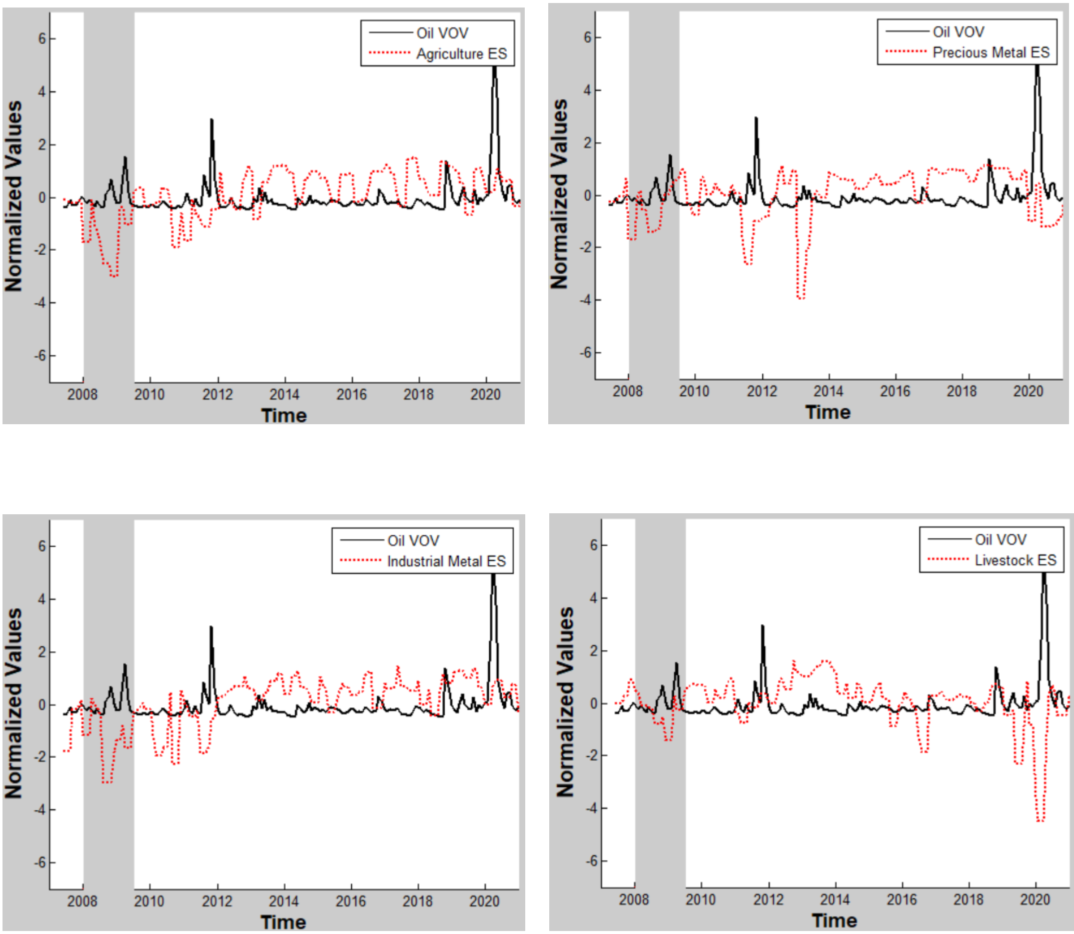


[2] We also use the standard deviation of the squared returns of log OVX as an alternative proxy for oil volatility of volatility, and the predictability of the proxy measure remains similar.



Panel B. Tail Risks Proxied by ES





Note: This figure shows the time-series plots of oil VOV and tail risk measures of commodities, including the aggregate commodity market (i.e., GSCI), energy, agriculture, precious metals, industrial metals, and livestock sector. Panel A and B are using tail risk measures proxied by VaR and ES, respectively. The sample period is from May 2007 to July 2021.

3. Empirical results

3.1 In-sample predictability

We measure conditional higher-moment risks based on the following predictive regression:

$$Tail_{i,t+1} = \alpha + \beta_1 vov_t + \beta_2 Tail_{i,t} + \epsilon_{t+1}, \tag{2}$$

where $Tail_{i,t+1}$ denotes commodity i's tail risk for month $t+1$, proxied by VaR or ES at 5% computed using returns from month $t+1$ to $t+3$ which is VaR_{t+3} or ES_{t+3} actually. We use vov_t with end of month t observations.

The results are reported in Table 1. Oil VOV shows negative and significant predictability for 1-period-ahead tail risks of the aggregate commodity market (i.e., GSCI), livestock, agricultural, and energy sector. In other words, an increase in oil VOV risk leads to higher downside risks for several other commodities and thus overall commodity market ultimately; our findings complement previous findings about the uncertainty of the oil market (e.g., Asai et al., 2020; Ji & Fan, 2012; Nazlioglu et al., 2013). These patterns indicate evidence that tail risk spills over from the crude oil market to other non-oil commodities and highlights the leading role of the crude oil market (e.g., Ahmed et al., 2022; Reboredo & Ugolini, 2016; Zhao et al., 2022).

Table 1: In-Sample Predictive Regression: Univariate Analysis

	Panel A: VaR				Panel B: ES			
	Const.	*vov*	Lagged term	Adj-R^2(%)	*Const.*	*vov*	Lagged term	Adj-R^2(%)
GSCI	-0.003***	0.319***	0.918***	80.37	-0.004***	0.518***	0.921***	77.35
(*t*-stat)	(-3.27)	(7.14)	(19.02)		(-3.55)	(8.16)	(20.34)	
Precious Metals	-0.004***	0.083**	0.807***	64.02	-0.005***	0.059	0.816***	65.69
(*t*-stat)	(-3.68)	(2.25)	(14.18)		(-4.19)	(1.20)	(18.98)	
Industry Metals	-0.002***	0.055*	0.892***	79.52	-0.003***	0.079***	0.887***	78.61
(*t*-stat)	(-2.84)	(1.92)	(17.68)		(-3.63)	(2.63)	(21.50)	
Livestock	-0.002**	0.325***	0.946***	75.32	-0.002*	0.299***	0.947***	76.53
(*t*-stat)	(-2.02)	(3.72)	(11.04)		(-1.93)	(3.36)	(12.74)	
Agriculture	-0.002**	0.054*	0.896***	80.20	-0.003***	0.061	0.879***	76.94
(*t*-stat)	(-2.40)	(1.89)	(16.57)		(-3.08)	(1.46)	(19.86)	
Energy	-0.004***	0.520***	0.914***	76.93	-0.005***	1.275***	0.973***	78.36
(t-stat)	(-3.18)	(6.05)	(16.38)		(-3.00)	(6.80)	(15.96)	

Note: This table reports shows the 1-month ahead predictability of oil volatility-of-volatility (VOV) for 1-period-ahead tail risks of aggregate commodity market (i.e., GSCI), energy, precious metals, and livestock sector. We consider two tail risk measures: VaR (Panel A) and ES (Panel B) at 5% level. Newey and West (1987) robust t-statistics, significant at the 1%, 5%, and 10% levels, denoted respectively by ∗∗∗, ∗∗, and ∗. The sample period is from May 2007 to July 2021.

The results are robust after controlling for other predictors, including oil market volatility, equity market volatility, equity market VOV, and a set of fundamental economic variables. The economic specification is as follows:

$$Tail_{i,t+1} = \alpha + \beta_1 vov_t + \beta_2 Tail_{i,t} + \beta_3 vol_t + \beta_4 VVIX_t + \beta_5 VIX_t + \gamma' x_t + \epsilon_{t+1}, \tag{3}$$

where vol is the oil market volatility, VVIX is the equity market, VIX is the equity market volatility, and x is the vector of fundamental economic variables including the term spread (i.e., TS), the default spread (i.e., DS), and the dividend-price ratio (i.e., DP). The results are presented in Table 2. The forecasting power of Oil VOV remains significant after controlling for oil volatility, equity VOV and fundamental economic variables. Notably, the oil volatility also shows significant predictability for the overall commodity market, and several individual sectors including livestock, agriculture, and energy. Our findings suggest that both volatility and tail risk spillovers from crude oil to other non-oil commodity markets. In sum, oil VOV contains unique information that cannot be covered by its equity counterpart and other volatility-related measures. Our findings highlight the prominent role of the crude oil market in disseminating information about economic conditions to other commodity markets.

Table 2: In-Sample Predictive Regression: Controlling Other Predictors

	Panel A: VaR									
	Const.	*vov*	Lagged term	OVX(10^3)	VVIX(10^3)	VIX(10^3)	TMS	DEF	PD	Adj-R^2(%)
GSCI	0.044	0.428***	1.018***	0.209*	0.061	0.040	0.102	-0.637**	-0.014*	75.18
(*t*-stat)	(1.45)	(4.60)	(11.89)	(1.73)	(1.16)	(0.39)	(1.16)	(-2.25)	(-1.90)	
Precious Metals	0.004	-0.010	0.768***	0.090	0.054	-0.215*	0.015	0.045	-0.004	60.58
(*t*-stat)	(0.13)	(-0.14)	(14.10)	(1.31)	(1.07)	(-1.79)	(0.24)	(0.20)	(-0.60)	
Industry Metals	0.044***	0.110**	0.838***	-0.023	0.097*	-0.099	-0.034	-0.168	-0.013***	77.28
(*t*-stat)	(2.66)	(2.12)	(12.63)	(-0.50)	(1.82)	(-1.07)	(-0.71)	(-1.10)	(-3.35)	
Livestock	0.003	0.314***	0.876***	-0.034	0.049*	-0.057	0.072**	0.013	-0.003	74.33
(*t*-stat)	(0.20)	(3.76)	(10.13)	(-1.04)	(1.79)	(-0.96)	(2.11)	(0.12)	(-0.69)	
Agriculture	0.058*	0.111**	0.737***	-0.025	0.202***	-0.298***	0.009	-0.201	-0.019**	73.40
(*t*-stat)	(1.65)	(2.54)	(10.86)	(-0.62)	(3.70)	(-2.76)	(0.20)	(-0.97)	(-2.19)	
Energy	0.069	1.425***	1.063***	0.389**	0.029	-0.009	0.184	-1.129**	-0.020*	77.67
(t-stat)	(1.52)	(7.87)	(11.86)	(2.14)	(0.40)	(-0.05)	(1.25)	(-2.15)	(-1.78)	
	Panel B: ES									
	Const.	*vov*	Lagged term	OVX(10^3)	VVIX(10^3)	VIX(10^3)	TMS	DEF	PD	Adj-R^2(%)
GSCI	0.025	1.004***	0.866***	-0.103	0.102*	-0.173	0.110	0.069	-0.010	67.09
(*t*-stat)	(0.65)	(5.42)	(17.25)	(-1.16)	(1.84)	(-1.45)	(0.99)	(0.25)	(-1.06)	
Precious Metals	0.023	-0.159*	0.766***	0.084	0.118*	-0.238	0.003	0.001	-0.010	60.86

(*t*-stat)	(0.52)	(-1.67)	(15.71)	(1.04)	(1.84)	(-1.47)	(0.04)	(0.00)	(-0.97)	
Industry Metals	0.065***	0.134**	0.677***	0.018	0.176**	-0.421**	-0.051	-0.225	-0.021***	65.76
(*t*-stat)	(2.87)	(2.09)	(8.10)	(0.33)	(2.00)	(-2.39)	(-0.71)	(-0.98)	(-3.40)	
Livestock	0.002	0.321***	0.814***	-0.061*	0.051	-0.083	0.083**	0.058	-0.003	68.92
(*t*-stat)	(0.09)	(2.88)	(9.44)	(-1.70)	(1.64)	(-1.18)	(1.97)	(0.38)	(-0.47)	
Agriculture	0.079*	0.261***	0.665***	-0.063	0.252***	-0.503***	0.008	-0.209	-0.025**	69.39
(*t*-stat)	(1.89)	(5.15)	(10.53)	(-1.45)	(3.66)	(-4.24)	(0.15)	(-0.82)	(-2.43)	
Energy	0.033	2.768***	0.972***	-0.090	0.067	-0.302	0.268	0.080	-0.012	74.32
(t-stat)	(0.54)	(4.37)	(10.04)	(-0.40)	(0.86)	(-1.32)	(1.36)	(0.15)	(-0.81)	

Note: This table reports shows the predictability of oil volatility-of-volatility (VOV) for 1-period-ahead tail risks of aggregate commodity market (i.e., GSCI), energy, precious metals, and livestock sector based on VaR (Panel A) or ES (Panel B) at 1% level. We control other predictors including. oil market volatility (OVX), VIX, VVIX, the term spread (i.e., TMS), the default spread (i.e., DEF), and the dividend-price ratio (i.e., DP). The t-statistics are computed according to Newey and West (1987), significant at the 1%, 5%, and 10% levels, and denoted respectively by ∗∗∗, ∗∗, and ∗. The sample period is from May 2007 to July 2021.

3.2 Robustness check

3.2.1 Other tail risk measures

In our main analysis, we use tail risk measures computed at the 5% level; therefore, we further check the in-sample predictability of VaR and ES computed at risk levels of 1%. The results are shown in Table 3. The tail risk spillovers can still be found from the crude oil market to other commodity markets such as energy, agriculture, livestock, and the overall commodity market, at a more extreme case. Our results indicate that when the economy faces extreme downside fluctuations, the crude oil market plays a prominent role in disseminating information about economic conditions to other commodity markets.[3]

[3] We also check the VaR and ES computed using historic 6-month daily returns, and the results remain robust. Details for the analysis will be available upon request.

Table 3: In-Sample Predictive Regression: Other Risk Level (VaR or ES at 1% Level)

	Panel A: VaR									
	Const.	*vov*	Lagged term	OVX(10^3)	VVIX(10^3)	VIX(10^3)	TMS	DEF	PD	Adj-R^2(%)
GSCI	0.044	0.428***	1.018***	0.209*	0.061	0.040	0.102	-0.637**	-0.014*	75.18
(*t*-stat)	(1.45)	(4.60)	(11.89)	(1.73)	(1.16)	(0.39)	(1.16)	(-2.25)	(-1.90)	
Precious Metals	0.004	-0.010	0.768***	0.090	0.054	-0.215*	0.015	0.045	-0.004	60.58
(*t*-stat)	(0.13)	(-0.14)	(14.10)	(1.31)	(1.07)	(-1.79)	(0.24)	(0.20)	(-0.60)	
Industry Metals	0.044***	0.110**	0.838***	-0.023	0.097*	-0.099	-0.034	-0.168	-0.013***	77.28
(*t*-stat)	(2.66)	(2.12)	(12.63)	(-0.50)	(1.82)	(-1.07)	(-0.71)	(-1.10)	(-3.35)	
Livestock	0.003	0.314***	0.876***	-0.034	0.049*	-0.057	0.072**	0.013	-0.003	74.33
(*t*-stat)	(0.20)	(3.76)	(10.13)	(-1.04)	(1.79)	(-0.96)	(2.11)	(0.12)	(-0.69)	
Agriculture	0.058*	0.111**	0.737***	-0.025	0.202***	-0.298***	0.009	-0.201	-0.019**	73.40
(*t*-stat)	(1.65)	(2.54)	(10.86)	(-0.62)	(3.70)	(-2.76)	(0.20)	(-0.97)	(-2.19)	
Energy	0.069	1.425***	1.063***	0.389**	0.029	-0.009	0.184	-1.129**	-0.020*	77.67
(*t*-stat)	(1.52)	(7.87)	(11.86)	(2.14)	(0.40)	(-0.05)	(1.25)	(-2.15)	(-1.78)	
	Panel B: ES									
	Const.	*vov*	Lagged term	OVX(10^3)	VVIX(10^3)	VIX(10^3)	TMS	DEF	PD	Adj-R^2(%)
GSCI	0.025	1.004***	0.866***	-0.103	0.102*	-0.173	0.110	0.069	-0.010	67.09
(*t*-stat)	(0.65)	(5.42)	(17.25)	(-1.16)	(1.84)	(-1.45)	(0.99)	(0.25)	(-1.06)	
Precious Metals	0.023	-0.159*	0.766***	0.084	0.118*	-0.238	0.003	0.001	-0.010	60.86
(*t*-stat)	(0.52)	(-1.67)	(15.71)	(1.04)	(1.84)	(-1.47)	(0.04)	(0.00)	(-0.97)	
Industry Metals	0.065***	0.134**	0.677***	0.018	0.176**	-0.421**	-0.051	-0.225	-0.021***	65.76
(*t*-stat)	(2.87)	(2.09)	(8.10)	(0.33)	(2.00)	(-2.39)	(-0.71)	(-0.98)	(-3.40)	
Livestock	0.002	0.321***	0.814***	-0.061*	0.051	-0.083	0.083**	0.058	-0.003	68.92
(*t*-stat)	(0.09)	(2.88)	(9.44)	(-1.70)	(1.64)	(-1.18)	(1.97)	(0.38)	(-0.47)	
Agriculture	0.079*	0.261***	0.665***	-0.063	0.252***	-0.503***	0.008	-0.209	-0.025**	69.39
(*t*-stat)	(1.89)	(5.15)	(10.53)	(-1.45)	(3.66)	(-4.24)	(0.15)	(-0.82)	(-2.43)	
Energy	0.033	2.768***	0.972***	-0.090	0.067	-0.302	0.268	0.080	-0.012	74.32
(*t*-stat)	(0.54)	(4.37)	(10.04)	(-0.40)	(0.86)	(-1.32)	(1.36)	(0.15)	(-0.81)	

Note: This table reports shows the predictability of oil volatility-of-volatility (VOV) for 1-period-ahead tail risks of aggregate commodity market (i.e., GSCI), energy, precious metals, and livestock sector based on VaR (Panel A) or ES (Panel B) at 1% level. We control other predictors including. oil market volatility (OVX), VIX, VVIX, the term spread (i.e., TMS), the default spread (i.e., DEF), and the dividend-price ratio (i.e., DP). The t-statistics are computed according to Newey and West (1987), significant at the 1%, 5%, and 10% levels, and denoted respectively by ∗∗∗, ∗∗, and ∗. The sample period is from May 2007 to July 2021.

3.2.2 Out-of-sample analysis

The in-sample predictability could be due to overfitting and thus might not imply out-of-sample predictability (Welch & Goyal, 2008). Thus, we conduct a group of statistical tests to assess the out-of-sample forecasting power of oil VOV. Following Campbell and Thompson (2008) and Rapach et al. (2010), the main measure we consider to assess out-of-sample forecasting performance is out-of-sample R-square (R^2_{OS}).[4] Additionally, we calculate McCracken's (2007) F-statistic (MSE-F), ENC-NEW statistic proposed by Clark and McCracken (2001) to obtain statistical inferences for the out-of-sample forecasting performance.[5] Out-of-sample statistics are constructed based on rolling windows with initial lengths of 60 months.[6]

Out-of-sample results are reported in Table 4. We observe that the strong in-sample predictability of oil VOV remains out-of-sample for GSCI and energy, as indicated by positive R^2_{OS}, significant values of the MSE-F and ENC statistics at the 5% level. Overall, we conclude that oil VOV predicts near-term tail risks of GSCI, and energy both in- and out-of-sample analysis.

Table 4: Out-of-Sample Test

	Panel A : VaR			**Panel B : ES**		
	OOS-R^2(%)	MSE-F	ENC-NEW	OOS-R^2(%)	MSE-F	ENC-NEW
GSCI	3.033	3.472***	25.066***	6.555	7.787***	6.441***
Energy	22.957	33.076***	30.360***	10.083	12.447***	10.124***
Precious Metals	-10.844	-10.859	3.671**	-6.343	-6.621	0.548
Industry Metals	-7.078	-7.338	6.492***	0.200	0.222	1.034
Agriculture	-0.224	-0.248	1.108	-6.064	-6.346	-2.054
Livestock	-7.962	-8.186	-2.660	-21.478	-19.625	-6.969

Note: This table reports shows the out-of-sample forecasting power of oil volatility-of-volatility (VOV) for 1-period-ahead tail risks of aggregate commodity market (i.e., GSCI), energy, precious metals, and livestock. We consider the following out-of-sample performance metrics: Out-of-sample R^2 (OOS-R^2), McCracken's (2007) F-statistic (MSE-F), and ENC-NEW statistic proposed by Clark and McCracken (2001). MSE-F and ENC-NEW, significant at the 1%, 5%, and 10% levels, and denoted respectively by ∗∗∗, ∗∗, and ∗. Out-of-sample statistics are constructed based on rolling windows with initial lengths of 60 months. The sample period for out-of-sample test is from May 2012 to July 2021.

[4] A positive R^2_{OS} suggests that the predicted model outperforms the historical average benchmark.

[5] Details for computation of the statistics can be found in Appendix.

[6] The rolling scheme is robust to structural changes or regime shifts.

4. Conclusion

In this paper, we find that oil VOV significantly predicts tail risks of the energy sector and the aggregate commodity market. The forecasting power of oil VOV remains robust after controlling for a set of predictors, including oil market volatility, equity market volatility, equity market VOV, and a set of fundamental economic variables. Notably, both oil volatility and VOV show significant predictability for several individual and aggregate commodity markets, highlighting the leading role of crude oil in commodity markets. Our findings are important for risk management and portfolio selection in commodity markets. More specifically, investors could obtain an optimal portfolio that effectively manages tail risks when investing in commodity markets, and this is mostly relevant during financial turmoil.

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Appendix

Out-of-Sample Evaluation Measures

R^2_{OS} measures the proportional reduction in the mean squared error for the OLS model with the predictor relative to the model excluding the predictor only. R^2_{OS} is computed as,

$$R^2_{OS} = 1 - \frac{MSE_A}{MSE_N}$$

where $MSE_A = \frac{1}{T}\sum_{t=1}^{T} e^2_{A_t}$ denotes the mean squared error for the OLS model with the predictor and $MSE_N = \frac{1}{T}\sum_{t=1}^{T} e^2_{N_t}$ denotes the mean squared error for the model excluding the predictor. T is the number of observations of the out-of-sample regressions.

The McCracken's (2007) *F*-statistic (MSE-F) is designed to test statistically whether an unrestricted model (models with the predictor) can beat a restricted model (the model excluding the predictor) in terms of our-of-sample forecasting performance. This measure is calculated as,

$$MSE - F = T \times \left(\frac{MSE_N - MSE_A}{MSE_A}\right)$$

We use the critical values derived by McCracken (2007) to obtain statistical inference for the MSE-F statistics. Another measure that we consider is ENC, which was also designed as a statistical test and proposed by Clark and McCracken (2001):

$$ENC = T \times \left(\frac{\sum_{t=1}^{T} e^2_{N_t} - e_{N_t} \cdot e_{A_t}}{MSE_A}\right)$$

The critical values shown in Clark and McCracken (2001) are used to obtain statistical inference.

Table A.1: Summary Statistics

	Mean	SD	Min	Max	Skew	Kurt
Panel A: Oil VOV	0.003	0.006	4.24e-4	0.070	8.229	85.271
Panel B: VaR (5%)						
GSCI	-0.032	0.018	-0.125	-0.011	-2.615	12.387
Precious Metals	-0.029	0.012	-0.080	-0.011	-1.272	4.836
Industry Metals	-0.029	0.012	-0.075	-0.011	-1.521	5.661
Livestock	-0.021	0.008	-0.057	-0.008	-2.204	10.743
Agriculture	-0.028	0.012	-0.065	-0.010	-1.039	3.681
Energy	-0.046	0.033	-0.257	-0.013	-4.222	25.558
Panel C: ES (5%)						
GSCI	-0.037	0.020	-0.125	-0.012	-2.243	9.592
Precious Metals	-0.034	0.017	-0.101	-0.014	-1.560	5.953
Industry Metals	-0.033	-0.077	-0.012	0.015	-1.141	3.747
Livestock	-0.023	0.009	-0.062	-0.009	-2.030	9.477
Agriculture	-0.032	0.014	-0.075	-0.010	-0.837	3.379
Energy	-0.054	0.041	-0.302	-0.015	-4.332	25.613

Note: This table reports descriptive statistics such as the mean (Mean), standard deviation (SD), minimum (Min), maximum (Max), skewness (Skew), and kurtosis (Kurt) for oil VOV, VaR and ES at 5% level for the aggregate commodity sector (GSCI), Energy, Precious Metals, Industry Metals, Agriculture, and Livestock sector. The sample period is from May 2007 to July 2021.

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INTEREST RATE HIKE AND THE INSTABILITY IN THE U.S. BANKING INDUSTRY

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Abstract

This paper investigates the effect of interest rate changes on the U.S. banks' performance captured by unrealised losses, investment securities allocation, and deposit withdrawal. We show that a sudden surge in interest rates could lead to massive losses, potentially erasing the market value of a bank's equity capital. We further show that the U.S. banks have switched more available-for-sale securities to held-to-maturity securities to reduce the realised losses. Moreover, such an increase in interest rates could prompt depositors, particularly those with uninsured deposits, to withdraw their funds. These findings align with bank-level data and highlight significant risks to banks, as evidenced by recent abrupt failures in the U.S. banking sector.

Keywords: bank collapse bank runs, deposit withdrawal, interest rate risk, securities reallocation

1. Introduction

A primary role of banks is to perform maturity transformation by accepting short-term deposits and providing long-term loans and investments. This process generates income for banks, as the long-term rates are typically higher than short-term rates, as explained in most textbooks (Drechsler et al, 2021). Nevertheless, this function also exposes banks to significant risk. If interest rates unexpectedly rise, the cost of borrowing can surpass the income earned from assets, resulting in a reduction of net interest margin (NIM) and a depletion of the bank's capital. This situation can be particularly dire for banks with low equity holdings, as an increase in interest rates can lead them to be at risk of collapse. Thus, interest rate risk is a fundamental concern in the banking industry.

However, in their recent study, Drechsler, Savov, and Schnabl (2021) argue that a large maturity mismatch does not expose banks to interest rate risk because "the deposit franchise gives banks market power over retail deposits, which allows them to borrow at rates that are both low and insensitive to market interest rates." According to the authors, depositors are unlikely to leave their bank even when better rates are available elsewhere, thus giving banks a competitive advantage. As a result, the authors conclude that interest rate risk does not pose a significant threat to banks. Nevertheless, the recent rapid collapses of some banks, such as Silicon Valley Bank and Signature Bank, cast doubt on the validity of this theory and its assumptions.

In this paper, we mainly employ aggregate data from the U.S. banking industry to examine the effect of interest rates on the U.S. banks' instability. We argue that a sudden increase in interest rates could lead to massive losses for banks. These losses could be realised or unrealised, but the market value of bank equity would drop significantly (English et al., 2018; Jiang et al., 2023; and Vo and Le, 2023).

Additionally, when banks face significant losses, depositors, especially those with uninsured deposits, could withdraw their deposits or reduce their deposits to the insured level. This deposit withdrawal could cause bank runs, especially for banks with concentrated depositors (Vo and Le, 2023).

The current evidence in the U.S. banking industry supports our arguments. A sudden increase in interest rates in 2022 resulted in huge realised and unrealised losses for banks. According to the current report by FDIC, the total unrealised losses on investment securities alone reached $690 billion in the third quarter of 2022.[1] Additionally, the total domestic deposits dropped by $304 billion in the second quarter and $185 billion in the third quarter of the same year. This situation has been more serious for small banks (e.g., regional and community banks) or for banks operating in narrow markets.

Analysing the Silicon Valley Bank's financial statements, Vo and Le (2023) identify four primary reasons leading to the bank's collapse: substantial losses in the bank's assets, the withdrawal of deposits, low capital, and inefficient risk management system. Similarly, Jiang et al. (2023) estimate the losses of bank assets in the U.S. and demonstrate that the losses can reach an average of 10% in 2022. Furthermore, they reveal that 10% of banks have greater unrealised losses and 10% of banks have lower capitalisation than those of SVB. This estimation indicates that many banks in the U.S. are at risk.

Our paper complements these results by investigating the effect of interest rate hikes on the unrealised losses from debt securities and deposit withdrawals at the aggregate level. We focus on debt securities because of three main reasons. First, debt securities are the main proportions of banks' total assets, accounting for about 25% in recent years. Second, the effects of interest rate on debt securities are similar those on loans and leases, which are the main categories in banks' total assets. Third, unlike unrealised losses on loans and leases, data on debt securities' unrealised losses are publicly available.

Using aggregate data of U.S. banks from 2009 to 2022, we first show that there is a positive relationship between interest rates and unrealised losses as well as deposit withdrawals. This relationship is particularly pronounced during the COVID-19 pandemic period of 2021-2022, which coincided with a surge in interest rates. Our multivariate analysis confirms that interest rates have a significant impact on unrealised losses. Furthermore, we find that U.S. banks have switched from available-for-sale (AFS) securities to held-to-maturity (HTM) securities as a means of reducing realised losses when interest rates increase. We also observe a positive effect of interest rates on deposit withdrawals. These findings suggest that rising interest rates expose U.S. banks to high unrealised losses on debt securities and significant deposit withdrawals, thereby increasing the risk of bank failure.

Employing bank-level data in the U.S., we find consistent conclusions: an increase in interest rates prompts banks to switch more to HTM securities by reducing investments in AFS securities. Moreover, banks tend to experience greater losses on these securities and higher uninsured deposit withdrawals. The securities switch is more pronounced for large banks or banks with low capital. However, the losses are more pronounced for small banks or banks with high capital or uninsured deposits. Additionally, large banks or banks with substantial uninsured deposits tend to experience higher uninsured deposit withdrawals.

To the best of our knowledge, this is the first paper examining the effects of the hikes in interest rates in 2022 on the U.S. banks' instability at the aggregate level. We show that an increase in interest rates is associated with high unrealised losses as well as deposit withdrawals. These results indicate that

[1] https://www.fdic.gov/analysis/quarterly-banking-profile/qbp/2022dec/.

interest rate hikes could pose significant risks to banks, as evidenced by the recent abrupt failures in the U.S. banking sector.

The remainder of the paper is as follows. In Section 2, we discuss sample selection and methodology. Section 3 analyses the effect of interest rates on unrealised losses on debt securities and deposit withdrawal at the aggregate level. Section 4 examines the effect of changes in interest rates on banks at the individual level. Finally, Section 5 concludes the paper.

2. Sample Selection and Methodology

We collect aggregate banking data from the Federal Deposit Insurance Corporation (FDIC). We define the debt securities ratio (SECU) as the proportion of total debt securities to the banks' total assets and the deposit ratio (DEPA) as the fraction of total deposit to total assets. Similarly, we compute the available-for-sale (AFS) securities, held-to-maturity (HTM) securities, and deposit ratios as the fractions of these variables over the banks' total assets. The unrealised losses on AFS securities ratio (UNLA) is the proportion of unrealised losses to AFS securities, the unrealised losses on HTM securities ratio (UNLH) is the fraction of unrealised losses to HTM securities, and the total unrealised losses on debt securities ratio (UNL) is the proportion of total unrealised losses to total debt securities.

To measure the switch from AFS to HTM securities, we consider two measures: (1) SWITCH as the difference between the change in HTM securities and the change in AFS securities scaled by 1 million, and (2) CDIFF as the change in the ratios of HTM securities over total securities to AFS securities to total securities. We define the insured deposit withdrawal ratio (CINW) as the negative percentage of the changes in insured deposits, and uninsured deposit withdrawal ratio (CUNINW) as the negative percentage of the changes in uninsured deposits. Similarly, the total deposit withdrawal (CDEPW) is the ratio of the negative change in total deposits.

We collect the fed funds effective rate (FED) from the Federal Research Bank of St. Louis, and Gross Deposit Product Ratio (GDP) and Customer Price Index (CPI) from the Bureau of Labor Statistics. We use CPI to measure the level of inflation in the U.S.[2]

To measure the effect of interest rates on banks' performance, we use the following base-line regression:

$$Y_t = \beta_1 CFED_t + \beta_2 MACRO_{t-1} + \beta_3 BANK_{t-1} + \varepsilon_t \tag{1}$$

where Y is either unrealised losses ratio (CUNL, CUNLA, or CUNLH), debt securities switches (SWITCH, or CDIFF), or deposit withdrawals (CINW, CUNINW, or CDEPW), FFUND is the fed funds effective rate, CFED is the fed funds effective rate, MACRO is a vector of macroeconomic variables, including GDP and CPI, and BANK is a vector of banks' characteristics, including the securities ratio (SECU) and the deposit ratio (DEPA).

We include GDP and CPI because they are important macro variables (e.g., Næs et al. 2011; and Vo 2014). We include banks' characteristics because they can affect unrealised losses and deposit withdrawals (Le, Narayana, and Vo 2016). Because these variables are time-series, we use unit root test (Augmented Dickey–Fuller test) to verify whether they are stationary. For non-stationary

[2] The results are qualitatively the same when we use the yield on 1-year Treasury bills or 3- year Treasury notes to substitute for the fed funds effective rate.

variables, we follow the literature (e.g., Næs et al. 2011, and Vo 2014) to detrend them before we include them into the regression model.

To robustly assess the impact of interest rate changes on bank performance, we collected bank-level data from the Federal Financial Institutions Examination Council (FFIEC) spanning 2009 to 2022. We excluded observations lacking information on total assets, total liabilities and equity capital, or deposits. We calculated the deposit ratio as the ratio of total deposits to total assets and return on assets (ROA) as the ratio of net income to total assets. The HTM securities ratio was determined by dividing HTM securities by total assets, and the AFS securities ratio was computed similarly. Uninsured deposits were defined as the ratio of time deposits exceeding $250,000 to total deposits. Due to the lack of disclosure by most banks regarding unrealised losses on HTM and AFS securities, we utilised realised losses on these securities as a proxy, calculating the loss ratio as the proportion of total realised losses on these securities relative to total assets.

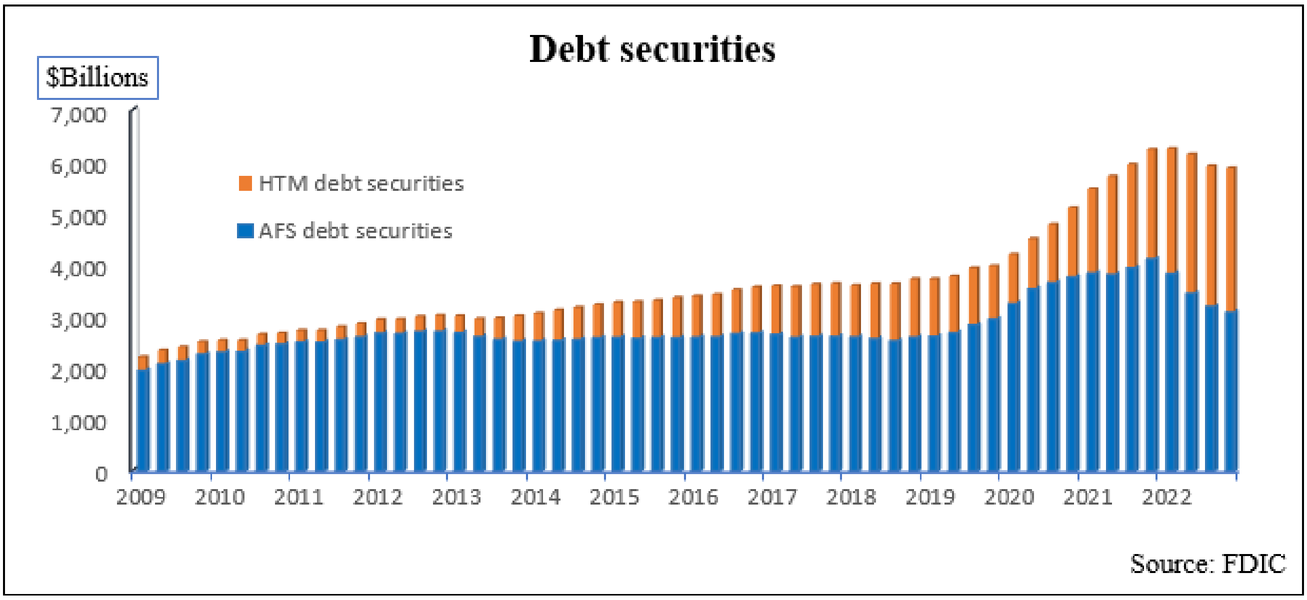
3. The Main Results

3.1 Descriptive Statistics

After the financial crisis of 2007-2009, the total assets of U.S. banks grew steadily from around $13 trillion in 2009 to $18.6 trillion by the end of 2019. However, this figure had increased tremendously during the COVID-19 pandemic, peaking in the second quarter of 2022 at $24 trillion. Similarly, total debt securities increased from $2.2 trillion at the beginning of 2009 to $4.0 trillion at the end of 2019. In just a short period of COVID-19 pandemic of 2020 -2022, total debt securities surged by $2.2 trillion, representing a growth of over 56%.

Among debt securities, the value of AFS securities were relatively stable until 2019. In contrast, the proportion of HTM securities grew slightly during this period. However, both categories of debt securities significantly increased from 2020 to 2021. AFS significantly grew to $4.11 trillion at the end of 2021 before decreasing to $3.08 trillion by the end of 2022. On the other hand, HTM securities increased from $1.03 trillion at the end of 2019 to $2.80 trillion by the end of 2022. These figures demonstrate that U.S. banks invested more in both types of debt securities from 2020 to 2021 but increasingly switched from AFS securities to HTM securities in 2021 and 2022. This trend is attributed to the rapid change in interest rates from the beginning of 2022.

Figure 1: Debt securities



Banks do not have to report unrealised losses from HTM securities but are required to recognise unrealised losses from AFS in their financial reports. As a result, by switching from AFS to HTM securities, banks' financial information appears more attractive to readers when interest rates increase. Additionally, this reallocation allows banks to have more favourable equity capital ratios, making them appear healthier.

During the financial crisis of 2007-2009, the unrealised losses of US banks reached a peak of $65 billion in the second quarter of 2008. After that, unrealised losses decreased and unrealised gains on investment securities started to appear from the second quarter of 2009. However, the unrealised losses surged in 2022, when the interest rates increased. The amounts of unrealised losses peaked at the highest ever of $690 billion in the second quarter of the same year.

Figure 2: Unrealised gains (losses) on investment securities

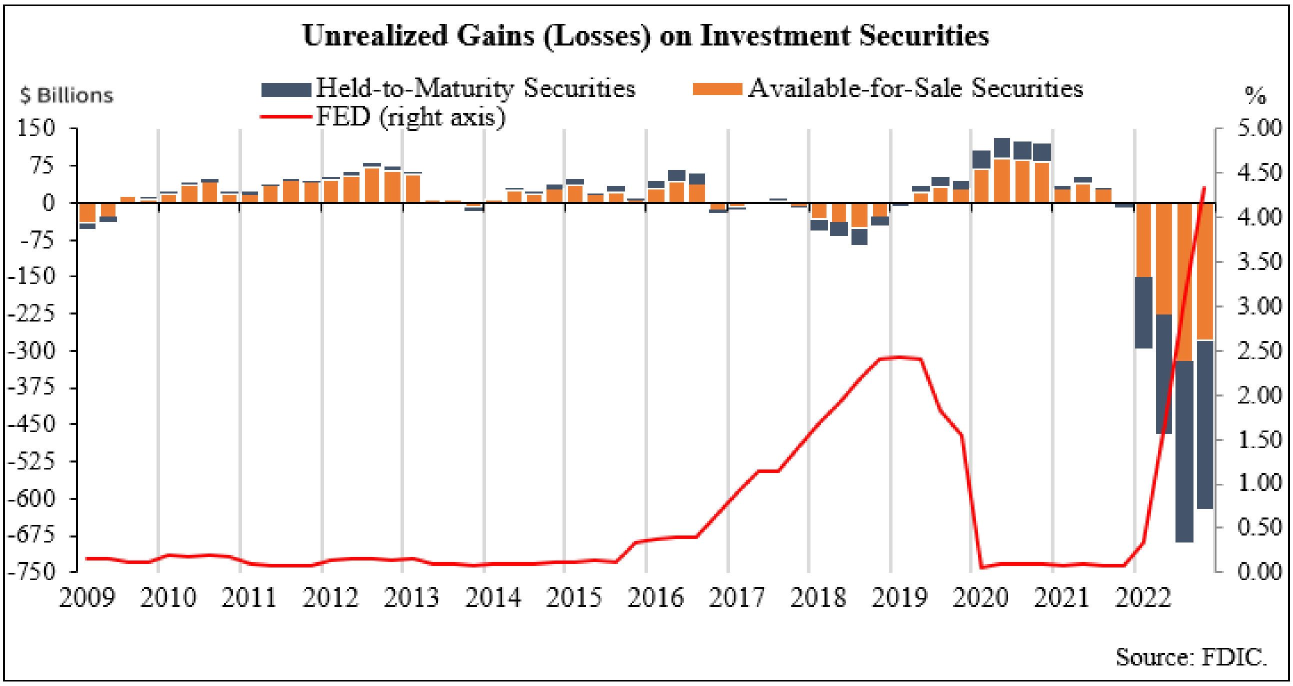
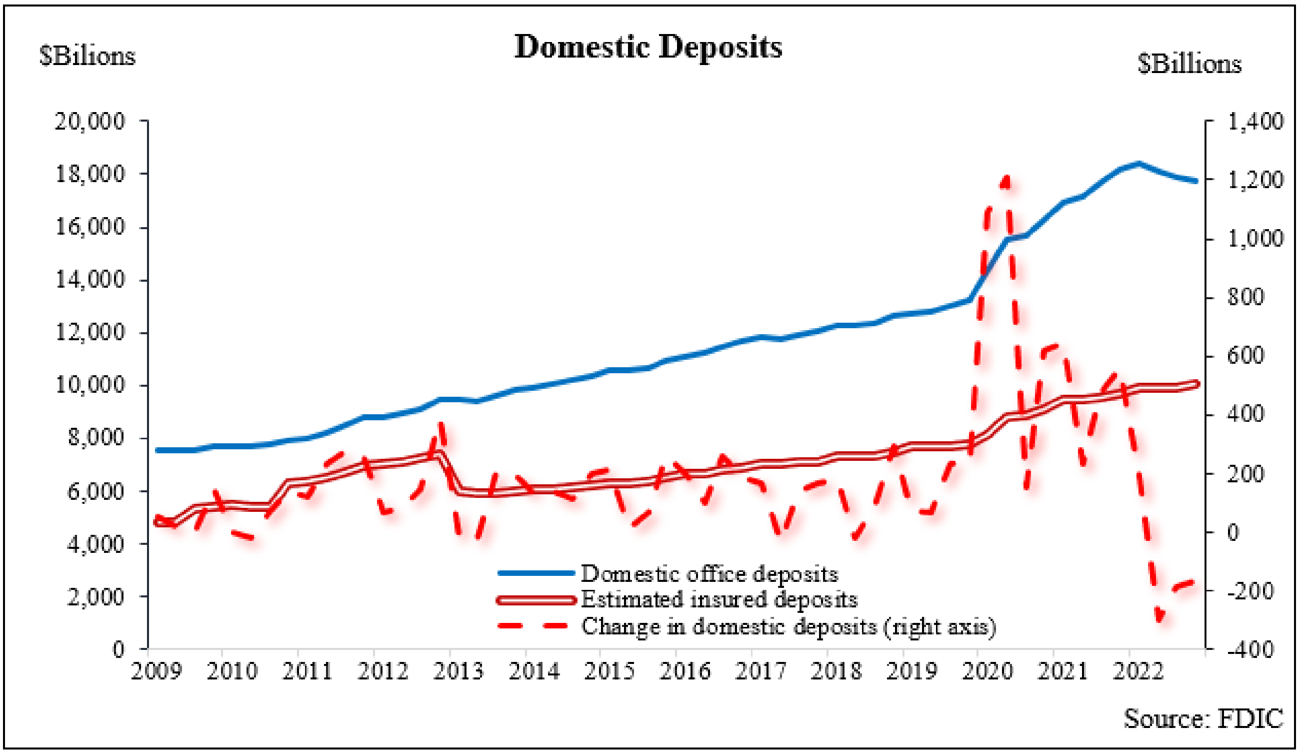


Figure 2 shows that before 2022, the unrealised gains (losses) mainly come from AFS securities, accounting for more than 85%. However, this trend was broken in 2022 when the unrealised losses on HTM securities counted for more than 50%. This evidence implies that HTM is more sensitive to the surge in interest rates than AFS securities.

For deposits, Figure 3 shows that the total domestic deposits, in general, increased steadily from 2009 until the beginning of 2022. However, these deposits experienced a significant surge from the first quarter of 2020 to the first quarter of 2022, before a substantial decrease afterward. In the second quarter of 2022, about $304 billion was withdrawn from the banking system. The withdrawals have occurred recently, with over $167 billion withdrawn every quarter.

Figure 2: Domestic deposits



3.2 Univariate Analysis

In this section, we quantify the relationship among variables used in our paper. Table 1 shows that the fed funds effective rate (CFED) is positively correlated with three measures of unrealised losses. The p-values of these correlations are smaller than 0.05, significant at the conventional levels. Consistent with the evidence in the previous section, these results indicate that the U.S. banks tend to have more unrealised losses when interest rates increase.

Table 1: Correlation Matrix

	CFED	CUNL	CUNLA	CUNLH	SWITCH	CDIFF	CINW	CUNINW	CDEPW	GDP	CPI	CSECU
CUNL	0.453***											
	(0.00)											
CUNLA	0.443***	0.997***										
	(0.00)	(0.00)										
CUNLH	0.415***	0.9421***	0.9193***									
	(0.00)	(0.00)	(0.00)									
SWITCH	0.672***	0.659***	0.651***	0.617***								
	(0.00)	(0.00)	(0.00)	(0.00)								
CDIFF	0.651***	0.631***	0.617***	0.598***	0.954***							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
CINW	0.114	0.077	0.079	0.090	0.177	0.127						
	(0.40)	(0.58)	(0.56)	(0.51)	(0.19)	(0.35)						
CUNINW	0.177*	0.020	0.019	-0.001	0.079	0.061	-0.824***					
	(0.09)	(0.88)	(0.89)	(0.99)	(0.56)	(0.65)	(0.00)					
CDEPW	0.570***	0.172	0.167	0.171	0.4693*	0.330**	0.368***	0.166				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.40)	(0.09)	(0.00)			
GDP	0.042	0.061	0.067	0.050	0.204	0.182	0.206	0.040	0.389***			
	(0.76)	(0.66)	(0.62)	(0.72)	(0.13)	(0.18)	(0.13)	(0.77)	(0.00)			
CPI	0.373***	0.504***	0.509***	0.397***	0.612***	0.607***	0.036	0.091	0.210	0.335**		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.79)	(0.50)	(0.12)	(0.01)		
CSECU	-0.202	-0.210	-0.226*	-0.127	-0.246*	-0.063	-0.119	0.072	-0.109	0.170	-0.039	
	(0.14)	(0.12)	(0.09)	(0.35)	(0.07)	(0.65)	(0.38)	(0.60)	(0.43)	(0.21)	(0.78)	
CDEPA	-0.215	-0.018	-0.024	0.039	-0.360**	-0.255*	-0.340**	-0.011	-0.577***	-0.303**	-0.226*	0.508***
	(0.11)	(0.90)	(0.86)	(0.78)	(0.01)	(0.06)	(0.01)	(0.94)	(0.00)	(0.02)	(0.09)	(0.00)

Note: This table reports the paired correlations among variables used in the paper. CUNL is the negative change in the banks' unrealised losses on investment securities, CUNLA is the negative change in the banks' unrealised losses on available-for-sale-securities, and CUNLH is the negative change in the banks' unrealised losses on held-to-maturity securities. SWITCH is the difference between the change in HTM securities and the change in AFS securities scaled by 1 million, CDIFF is the change in the ratios of HTM securities to AFS securities. CINW is the banks' insured deposit withdrawal, CUNINW is the banks' uninsured deposit withdrawal, and CDEPW is the banks' total deposit withdrawal. CFED is the change in the fed funds effective rate, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table 1 also documents that fed funds effective rate positively correlated with both measures of the switch in debt securities. In contrast, the relationship between the fed funds effective rate and each measure of deposit withdrawal is divergent. While the relationship between the fed funds effective rate and insured deposit withdrawals is insignificant, the relationship between this rate and total deposit withdrawals is significantly positive. This means that when interest rates increase, uninsured depositors withdraw their funds from the banking industry.

Table 1 also presents the correlation between our main variables and other controlled variables. The relationship between CPI and each measure of unrealised losses is significantly positive, implying that the U.S. banks tend to experience high unrealised losses when inflation rate increases. In contrast, the GDP growth is not significantly correlated with the banks' losses.

3.3 Multivariate Analysis

To further investigate the effects of interest rates on bank performance, we employ the regression model (1). The results, reported in Table 2, show that there is a positive correlation between the change in fed funds effective rate and three measures of unrealised losses. The coefficients of these correlations have p-values of less than 0.05, signifying significance at the 5% level. Inconsistent with the argument in Drechsler et al., (2021)'s article, this result suggests that as interest rates rise, U.S. banks are more likely to experience greater unrealised losses. In terms of magnitude, if fed funds rate increases by one standard deviation of the change in this rate (0.39%), the unrealised losses will increase by 2.92%.

Table 2: Interest Rate and Unrealised Losses

	$CUNL_t$	$CUNLA_t$	$CUNLH_t$
$CFED_t$	0.001**	0.001**	0.001**
	(0.031)	(0.044)	(0.029)
GDP_{t-1}	-0.000	-0.000	-0.000
	(0.599)	(0.601)	(0.843)
CPI_{t-1}	0.000***	0.000***	0.000
	(0.008)	(0.005)	(0.177)
$CSECU_{t-1}$	0.000	0.000	-0.000
	(0.575)	(0.552)	(0.987)
$CDEPA_{t-1}$	0.000	-0.000	0.000
	(0.960)	(0.973)	(0.717)
Intercept	-0.000	-0.000	-0.000
	(0.152)	(0.122)	(0.463)
N	56	56	56
Adj. R^2	0.2612	0.2684	0.1268

Note: This table reports the results from the regression of the banks' unrealised losses on the change in the interest rates and other variables. CUNL is the negative change in the banks' unrealised losses on investment securities, CUNLA is the negative change in the banks' unrealised losses on available-for-sale- securities, and CUNLH is the negative change in the banks' unrealised losses on held-to-maturity securities. CFED is the change in the fed funds effective rate, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively

We have also investigated the impact of interest rates on the switch in debt securities. The findings presented in Table 3 indicate that this effect is positive, with p-values of the coefficients smaller than 0.01, signifying significance at the 1% level. Additionally, the table shows that the U.S. banks tend to switch from available-for-sale (AFS) securities to held-to-maturity (HTM) securities when the inflation rate rises.

Table 3: Interest Rate and the Switch between HTM and AFS securities

	$SWITCH_t$	$CDIFF_t$
$CFED_t$	24.982***	5.061***
	(0.000)	(0.000)
GDP_{t-1}	0.118	0.014
	(0.686)	(0.815)
CPI_{t-1}	2.246**	0.435**
	(0.034)	(0.048)
$CSECU_{t-1}$	2.070	0.494
	(0.635)	(0.587)
$CDEPA_{t-1}$	2.615	0.798
	(0.399)	(0.219)
Intercept	-0.043*	0.000
$CFED_t$	(0.072)	(0.971)
N	56	56
Adj. R^2	0.4868	0.4615

Note: This table reports the results from the regression of the switch between HTM and AFS securities on the change in the interest rates and other variables. SWITCH is the difference between the change in HTM securities and the change in AFS securities scaled by 1 million, CDIFF is the change in the ratios of HTM securities to AFS securities. CFED is the change in the fed funds effective rate, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table 4 presents the results of the regression analysis for deposit withdrawals with the change in the fed funds effective rate and other controlled variables. The findings in the table indicate that the effect of the fed funds effective rate on insured deposit withdrawals is not significant. In contrast, the fed funds effective rate has a significant and positive correlation with the withdrawal in either total deposits or uninsured deposits. This implies that as interest rates rise, uninsured depositors tend to withdraw their funds from the banking industry, resulting in a decrease in the banks' total deposits.

Table 4: Interest Rate and the change in deposit

	$CINW_t$	$CUNINW_t$	$CDEPW_t$
$CFED_t$	0.869	8.157**	3.445***
	(0.572)	(0.042)	(0.000)
GDP_{t-1}	0.119	-0.328	-0.002
	(0.206)	(0.172)	(0.966)
CPI_{t-1}	0.069	-1.189	-0.278
	(0.836)	(0.166)	(0.136)
$CSECU_{t-1}$	-3.769***	13.231***	0.674
	(0.009)	(0.001)	(0.221)
$CDEPA_{t-1}$	2.647***	-8.582***	0.019
	(0.010)	(0.001)	(0.961)

Intercept	-0.022***	0.004	-0.016***
	(0.005)	(0.846)	(0.000)
N	56	56	56
Adj. R^2	0.0844	0.2081	0.3522

Note: This table reports the results from the regression of the banks' deposit withdrawal on the change in the interest rates and other variables. CINW is the banks' insured deposit withdrawal, CUNINW is the banks' uninsured deposit withdrawal, and CDEPW is the banks' total deposit withdrawal. CFED is the change in the fed funds effective rate, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Overall, the findings from Table 1 to Table 4 suggest that an increase in interest rates leads to substantial unrealised losses on investment securities for U.S. banks. Additionally, the results indicate that a rise in interest rates is linked to the withdrawal of uninsured deposits, which represent roughly 45% of total deposits held by banks. These results align with recent research on banking fragility, such as the studies conducted by Jiang et al. (2023) and Vo and Le (2023). The results suggest that U.S. banks may be vulnerable to risk during periods of surging interest rates.

4. Bank-level Analysis

Our primary analysis examines the impact of interest rate hikes on bank performance at the aggregate level. To ensure the robustness of our findings, we extend our investigation to the bank level by modifying regression model (1) as follows:

$$\text{Perform}_{i,t} = \beta_1\Delta\text{FED}_t + \beta_2\text{MACRO}_{t-1} + \beta_3\text{ABANK}_{t-1} + \beta_4\text{BANK}_{i,t-1} + \beta_5\text{BANK-DUMM}_i + \varepsilon_t \tag{2}$$

where Perform is a measure of bank performance, including debt securities switches (the difference between the change in HTM securities and change in AFS securities), change in HTM securities, change in AFS securities, losses on HTM and AFS securities, realised losses on both HTM and AFS securities ratio, and change in uninsured deposit ratio. ΔFED is the change in the fed funds effective rate in percentage, MACRO is a vector of macroeconomic variables, including GDP and CPI, and ABANK is a vector of banks' characteristics at aggregate level, including the securities ratio (SECU) and the deposit ratio (DEPA). BANK is a vector of bank-level characteristics, which consists of the logarithm of total assets, ROA, deposit ratio, capital ratio, HTM securities ratio, and AFS securities ratio.

Table 5 presents the results from regression model (2). The first column indicates that the coefficient for the change in interest rate is positive and statistically significant at the 1% level (p-value = 0.00). This suggests that as interest rates rise, banks tend to increase their holdings of HTM securities. Notably, the change in interest rate is significantly positively correlated with changes in HTM securities and negatively correlated with AFS securities. These findings imply that higher interest rates prompt banks to invest more in HTM securities while reducing their AFS securities holdings. Additionally, the results indicate that banks experience greater losses, particularly in AFS securities, and that depositors are more likely to withdraw uninsured deposits when interest rates increase. The coefficient for the change in interest rate is negative and significant at the 1% level (p-value = 0.00).

Table 5: Interest Rate and Bank Performance

	ΔSE_t	ΔHTM_t	ΔAFS_t	$\Delta LOSS_t$	$\Delta UNDEP_t$
ΔFED_t	0.001***	0.001***	-0.001***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP_t	0.002**	0.002***	-0.001	-0.000***	0.003***
	(0.029)	(0.000)	(0.454)	(0.000)	(0.000)
CPI_t	-0.127***	0.027***	0.155***	0.001***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CSECU_t$	-0.479***	-0.081***	0.397***	0.007***	-0.118***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CDEPA_t$	0.007	0.002	-0.004	-0.007***	-0.122***
	(0.574)	(0.592)	(0.676)	(0.000)	(0.000)
LAT_{t+1}	0.003***	0.000	-0.003***	-0.000***	0.001***
	(0.000)	(0.625)	(0.000)	(0.000)	(0.000)
ROA_{t+1}	-0.032*	-0.009	0.023	0.011***	0.017**
	(0.050)	(0.160)	(0.110)	(0.000)	(0.024)
DEP_{t+1}	-0.020***	0.004***	0.024***	0.000	-0.010***
	(0.000)	(0.000)	(0.000)	(0.784)	(0.000)
CAP_{t+1}	0.011*	-0.019***	-0.031***	-0.001***	-0.001
	(0.088)	(0.000)	(0.000)	(0.000)	(0.601)
HTM_{t+1}	-0.063***	-0.067***	-0.004	-0.000***	-0.006***
	(0.000)	(0.000)	(0.269)	(0.000)	(0.000)
AFS_{t+1}	0.086***	0.003***	-0.083***	-0.000***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$UNDEP_{t+1}$	0.007**	-0.004***	-0.011***	-0.000***	-0.140***
	(0.036)	(0.001)	(0.000)	(0.000)	(0.000)
Intercept	-0.030***	-0.001	0.028***	0.001***	0.008***
	(0.000)	(0.520)	(0.000)	(0.000)	(0.001)
N	300,349	300,349	300,349	300,349	300,349
Adj. R^2	0.0432	0.0334	0.0506	0.0201	0.0822

Note: This table reports the results from the regression model (2). ΔFED is the change in the fed funds effective rate in percentage, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. SE is the switch from AFS to HTM securities, HTM is the HTM securities ratio, AFS is the AFS securities ratio, LOSS is the realised losses on both HTM and AFS securities, UNDEP is uninsured deposit ratio, LAT is the logarithm of total assets, and CAP is the capital ratio. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

To further explore how changes in interest rates affect bank performance, we examine the moderating role of specific bank characteristics. We modify regression model (2) by incorporating interactions between the change in interest rate and key bank characteristics, such as size (logarithm of total assets), capital ratio, and uninsured deposit ratio. Our focus is on the coefficients of the change in interest rates and these interaction terms.

Column 1 of Table 6 reveals that the coefficient for the change in interest rates becomes significantly negative, while the interaction term is significantly positive. This indicates that larger banks are more inclined to shift towards HTM securities by reducing their AFS securities investments in response to rising interest rates. However, columns (2) and (3) suggest that smaller banks have incurred higher securities losses, whereas larger banks face greater withdrawals of uninsured deposits. This observation aligns with the notion that larger banks typically attract substantial depositors with more uninsured deposits and maintain more diversified asset portfolios.

Table 6: Interest Rate, Bank Characteristics, and Bank Performance

	ΔSE_t	$\Delta LOSS_t$	$\Delta UNDEP_t$	ΔSE_t	$\Delta LOSS_t$	$\Delta UNDEP_t$	ΔSE_t	$\Delta LOSS_t$	$\Delta UNDEP_t$
ΔFED_t* LAT_{t+1}	0.001***	-0.000*	-0.000***						
	(0.000)	(0.066)	(0.000)						
ΔFED_t* CAP_{t+1}				-0.017***	0.000***	0.001			
				(0.000)	(0.001)	(0.373)			
ΔFED_t* $UNDEP_{t+1}$							-0.002	0.000**	-0.002*
							(0.498)	(0.030)	(0.086)
ΔFED_t	-0.005***	0.000**	0.002***	0.003***	-0.000*	-0.001***	0.001***	0.000	-0.000***
	(0.000)	(0.017)	(0.000)	(0.000)	(0.096)	(0.000)	(0.000)	(0.207)	(0.000)
GDP_t	0.003**	-0.000***	0.003***	0.002**	-0.000***	0.003***	0.002**	-0.000***	0.003***
	(0.022)	(0.000)	(0.000)	(0.025)	(0.000)	(0.000)	(0.029)	(0.000)	(0.000)
CPI_t	-0.129***	0.001***	-0.014***	-0.129***	0.001***	-0.015***	-0.128***	0.001***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CSECU_t$	-0.471***	0.007***	-0.120***	-0.476***	0.007***	-0.118***	-0.478***	0.007***	-0.118***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CDEPA_t$	0.006	-0.007***	-0.122***	0.010	-0.007***	-0.122***	0.007	-0.007***	-0.122***
	(0.610)	(0.000)	(0.000)	(0.393)	(0.000)	(0.000)	(0.563)	(0.000)	(0.000)
LAT_{t+1}	0.002***	-0.000***	0.001***	0.003***	-0.000***	0.001***	0.003***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t+1}	-0.029*	0.011***	0.016**	-0.031*	0.011***	0.017**	-0.032*	0.011***	0.017**
	(0.074)	(0.000)	(0.033)	(0.055)	(0.000)	(0.025)	(0.051)	(0.000)	(0.024)
DEP_{t+1}	-0.021***	0.000	-0.010***	-0.020***	0.000	-0.010***	-0.020***	0.000	-0.010***
	(0.000)	(0.739)	(0.000)	(0.000)	(0.740)	(0.000)	(0.000)	(0.768)	(0.000)
CAP_{t+1}	0.010	-0.001***	-0.001	0.015**	-0.001***	-0.002	0.011*	-0.001***	-0.001
	(0.127)	(0.000)	(0.705)	(0.027)	(0.000)	(0.559)	(0.087)	(0.000)	(0.605)
HTM_{t+1}	-0.063***	-0.000***	-0.005***	-0.063***	-0.000***	-0.006***	-0.063***	-0.000***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AFS_{t+1}	0.085***	-0.000***	-0.004***	0.085***	-0.000***	-0.004***	0.085***	-0.000***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$UNDEP_{t+1}$	0.007**	-0.000***	-0.140***	0.007**	-0.000***	-0.140***	0.007**	-0.000***	-0.139***
	(0.020)	(0.000)	(0.000)	(0.031)	(0.000)	(0.000)	(0.029)	(0.000)	(0.000)
Intercept	-0.027***	0.001***	0.007***	-0.029***	0.001***	0.008***	-0.030***	0.001***	0.008***
	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
N	300,349	300,349	300,349	300,349	300,349	300,349	300,349	300,349	300,349
Adj. R^2	0.0435	0.0201	0.0823	0.0434	0.0202	0.0822	0.0432	0.0201	0.0822

Note: This table reports the results from the regression model (2). ΔFED is the change in the fed funds effective rate in percentage, GDP is the GDP growth rate, CPI is the CPI index, CSECU is the change in the banks' securities to total assets ratio, and CDEPA is the change in the banks' deposit to total assets ratios. SE is the switch from AFS to HTM securities, HTM is the HTM securities ratio, AFS is the AFS securities ratio, LOSS is the realised losses on both HTM and AFS securities, UNDEP is uninsured deposit ratio, LAT is the logarithm of total assets, and CAP is the capital ratio. The *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table 6 also shows that banks with low capital tend to switch more to HTM securities by reducing investments in AFS securities to reduce realised losses on these securities. Moreover, banks with a high uninsured deposit ratio tend to experience higher losses and higher uninsured deposit withdrawals when interest rates increase.

5. Conclusion

This paper investigates the impact of interest rate on the U.S. banks' performance measured by the unrealised losses on debt securities and deposit withdrawals at the aggregate level since the end of the financial crisis of 2007-2009. We first show that the U.S. banks only significantly invested in debt securities during the COVID-19 pandemic. The total value of investment securities grew at over 56% during the 2020-2021 period and started to decline in 2022 when interest rates surged. Among these securities, HTM ones nearly tripled, and they are still growing in 2022 while AFS securities have dropped. These results indicate that there exists a switch in banks' securities investments. Although the banks can hide unrealised losses on these securities, this shift makes banks' balance sheets more attractive as well as reduces the pressure on maintenance of banks' capital requirement.

Second, our analysis reveals that unrealised losses on U.S. banks' debt securities surged in 2022, peaking at an all-time high of $690 billion in the second quarter of the year. We also observed a significant shift in the unrealised losses (or gains) on available-for-sale (AFS) and held-to-maturity (HTM) securities. Prior to the COVID-19 pandemic, AFS securities accounted for over 85% of unrealised losses (or gains), but during the pandemic, this figure decreased to less than 50%. In contrast, HTM securities showed a sharp increase in unrealised losses (or gains), exceeding 50% during the same period. These results suggest that HTM securities are more sensitive to interest rate surges than AFS securities.

Third, we document that total domestic deposits increased significantly from 2020 to the first quarter of 2022, but have since largely dropped, mainly due to a decline in uninsured deposits. However, insured deposits have continued to grow during the COVID-19 pandemic.

Fourth, using the regression model, we show that interest rates are significantly correlated with the banks' unrealised losses. Moreover, we also document that uninsured depositors withdraw their funds from banking system when interest rates increase. As a result, the total deposits are negatively related to interest rates.

Finally, we reinforce these findings through an analysis of bank-level data, yielding consistent results. An increase in interest rates encourages banks to reallocate investments from AFS securities to HTM securities. Additionally, banks face increased losses on these securities and greater withdrawals of uninsured deposits. This shift toward HTM securities is more significant among large banks or those with lower capital. Conversely, smaller banks or institutions with higher capital or uninsured deposits incur more substantial losses. Furthermore, large banks or those with a higher proportion of uninsured deposits are particularly vulnerable to elevated uninsured deposit withdrawals.

The findings in our paper provide implications for policymakers. First, a surge in interest rates could lead to significant losses for banks. Second, uninsured depositors may withdraw their funds from the banking system as interest rates rise. Both high losses and deposit withdrawals can pose risks to banks, potentially causing some banks to fail if they do not manage their assets and liabilities properly.

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CLIMATE RISK AND THE PREDICTABILITY OF JUMPS IN GREEN ASSETS

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Abstract

This paper shows that climate risk can help predict the size and direction of intraday jumps in green assets, both in and out-of-sample. Using tick data to capture the size and intensity of intraday jumps, we find that news that relate to transition climate risk including international summits and climate policy, particularly those that could be interpreted as bad news for brown industries, are the most dominant predictors of jumps in green assets compared to proxies of physical climate risks. Our findings provide a novel perspective to the role of climate risk as a driver of idiosyncratic tail risk and jump innovations in green assets and imply that pricing models that incorporate jump risk as a risk factor can be improved by exploiting the predictive power of climate risk over jump dynamics.

Keywords: Climate risk, stock market jumps, green investments, intraday returns

1. Introduction

Modeling jumps in stock prices has significant implications for the pricing and hedging in financial markets. Jumps refer to sudden and infrequent movements of large magnitude in the path of stock prices and the literature provides ample evidence that systematic jump risk accounts for a large percentage of the total equity risk premium, establishing a link between jump risk and idiosyncratic tail risk that is undiversifiable (Begin et al., 2020), while other works show that jump measures obtained from high frequency data can improve stock volatility forecasts (Bu et al., 2023). Considering investors should be rewarded for bearing systematic risk and the evidence that jumps serve as a systematic risk factor in expected stock returns (Dunham and Friesen, 2007), predictability of jumps becomes an important consideration for not only asset pricing, but also in portfolio allocation strategies. The main contribution of this study is to extend the study of jumps to the emerging literature on climate finance and examine the predictive role of climate risk on jumps in green assets.

A growing number of recent works on climate finance establish a link between climate risk and the cross-section of equity returns (Bolton and Kacperczyk, 2021; Faccini et al., 2023), while others examine green investments in the context of hedging against climate risks (Cepni et al., 2022). None of these studies, however, has examined the role of climate risk in the context of jump risk although a growing literature highlights climate policy uncertainty as a driver of price dynamics in green equities (Bouri et al., 2022). While stock price jumps can be associated with firm-specific events, unexpected market news or large arbitrage activities (Kong et al., 2021), the literature provides ample evidence that these discontinuous fluctuations in prices can have serious implications for pricing and asset allocation, which is an important consideration for the viability of sustainable investments. Looking ahead, our analysis shows that both the direction and size of price jumps in green markets can indeed be predicted via measures of climate risk, both in- and out-of-sample. We find that news captured by transition climate risk proxies including international summits and climate policy, particularly those that could be interpreted as bad news for brown industries, are the most dominant predictors of jumps in green assets compared to proxies of physical climate risks, in line with the evidence that the risk of government interventions, rather than the direct risks from climate change, serves as a more dominant driver of expected returns in equities. While international summits provide greater predictive contribution for positive jumps, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies. Considering that a significant portion of idiosyncratic risk in stocks can be attributed to jump risk (Begin et al., 2020), our findings suggest that measures of climate risk can help improve pricing models in green investments via its interaction with idiosyncratic volatility, thus opening a new line of explanation to the risk-return tradeoffs in green assets.

The remainder of the paper is organised as follows. Section 2 outlines the data and methodology. Section 3 presents the empirical results and Section 4 concludes with a discussion of the implications of our findings.

2. Data and Methodology

2.1 Data

We utilise tick data, obtained from the Thomson Reuters Tick History (TRTH) database, for the Invesco Global Clean Energy ETF that is comprised of companies engaged in cleaner energy and conservation globally. Also utilised by other works including Bouri et al. (2022) as a proxy for green technology stocks, this fund captures price movements in stocks that are engaged in the advancement of cleaner energy and conservation. Formed to replicate the performance of the WilderHill New Energy Global Innovation Index, the fund's holdings include leaders in renewable energy technologies from a diverse set of industries including industrials, energy, information technology, utilities, and consumer discretionary. The data cleaning process involves consolidating duplicate quotes and transactions by replacing them with a single entry using the mean bid price, ask price or transaction price and cumulated trading volumes. Negative bid-ask spread entries are removed.

To assess climate-related risks, we use the climate indices developed by Faccini et al. (2023) via textual and narrative analysis of Reuters climate-change news. The authors compile a corpus of more than 13 million articles published in Reuters over the period Jan. 2000 to Dec. 2018. After an initial filtering based on the language, multiple entries and subsequent corrections in the articles, the authors end up with a sample of about seven million articles covering a diverse set of topics that include sports, technology, politics, finance, among others. Since the goal is to assess the coverage of climate related news in these articles, they discard irrelevant ones and keep only those in which the bigrams "climate change" or "global warming" occur at least once, yielding a final sample of roughly 34,000 articles. Since this final sample covers a rather heterogeneous set of articles related to climate change, the authors group the news into specific climate subcategories via the Latent Dirichlet Allocation method proposed by Blei et al. (2003). In this procedure, the collection of articles in the final sample is scanned based on a vocabulary of over 6,000 unique words to (i) decompose the entire textual corpus into topics identified by the machine learning algorithm that dissects textual heterogeneity into topics; and (ii) express each article as a probability weighted average of topics where each topic share reflects the intensity (frequency) by which a topic appears in that article. Once the machine learning algorithm delivers the topics, the authors then label them based on the words that appear most frequently. In the case of Faccini et al. (2023), the LDA model classifies the unique words into 25 different topics and by applying several criteria, the authors classify the topics into four general headings, namely natural disasters, global warming, U.S. climate policy (actions and debate), and international summits. Summing the topic shares across all the articles published in a given day, the authors then generate a measure of the intensity of news coverage for a given topic in a given day.

Following the argument by Engle et al. (2020) that the disclosure of news reveals risks for firms and investors, Faccini et al. (2023) interpret the daily time series of media news coverage of each topic as a measure of climate risk associated with the occurrence of natural disasters, global warming, U.S. climate policy (actions and debate), and international summits. In their setting, an increase in news coverage is interpreted as either an increase in the number of articles published or an increase in media attention to a particular climate topic. The authors argue that news about natural disasters and global warming typically signal adverse effects on the economy as such news raise media attention whenever it is a source of concern (Engle et al., 2020). Similarly, international summits also signal adverse effects on the economy as these meetings are typically associated with discussions on a global tax on pollutants, which is bad news for firm profitability. Climate policy, however, is relatively harder to interpret as one might argue that increased news coverage of the U.S. political debate on climate policy may reflect good or bad news for the economy depending on which party, Democrats or Republicans, holds the power. Nevertheless, their analysis shows that these climate risk proxies do not confound the effects associated with other sources of uncertainty like economic policy uncertainty or other political risks and are interpreted as risk factors based on their direct effects on stakeholders. Based on the availability of the climate risk series and intraday ETF data, the sample period spans from June 2007 to November 2019.

Intraday price jumps are identified following Lee and Mykland (2008). The observed log mid-prices *p* are generated in a continuous time Brownian semi-martingale process with finite activity jumps:

$$dp(s) = \mu(s)ds + \sigma(s)dW(s) + k(s)dq(s) \tag{1}$$

where $\mu(s)$ is the drift term with a continuous and locally finite variation sample path, $\sigma(s)$ is a strictly positive spot volatility process, and $W(s)$ is a standard Brownian motion. The component $k(s)dq(s)$ corresponds to the pure jump component, where $dq(s) = 1$ if there is a jump at time s and 0 otherwise, and $k(s)$ is the jump size. Following this framework, each trading day *i* consists of *M* equally spaced intraday returns where $r_{t,i}$ is the log return of the mid-quote in the interval *t* of the day *i*. The associated test statistic for jumps in $r_{t,i}$ is the absolute return standardised with a jump-robust estimate of the average daily volatility ξ_t together with an intraday volatility factor $f_{t,i}$: $J_{t,i} = \frac{|r_{t,i}|}{\xi_t \, f_{t,i}}$ where ξ_t is estimated as the square root of the realised bipower variation per Barndorff-Nielsen and Shephard (2006) and $f_{t,i}$, is the truncated maximum likelihood periodicity estimate per Boudt et al. (2011). Lee and Mykland (2008) propose to reject the null of no jump on $r_{t,i}$ if: $J_{t,i} > G^{-1}(1-\alpha)S_n + C_n$) where $G^{-1}(1-\alpha)$ is the $(1-\alpha)$ quantile function of the standard Gumbel distribution and □ $C_n = (2log\ n)^{0.5} - \frac{log\ (\pi) + log\ (\log n)}{2(2log\ n)^{0.5}}$ and $S_n = \frac{1}{(2logn)^{0.5}}$ where *n* is the total number of observations (i.e., M × T). Following Boudt and Petitjean (2014), we reject the null of no jump if $J_{t,i} > S_n \beta^* + C_n{}^{\beta^*}$ with β^* such that $exp\ (-exp^{\beta^*}) = 1-\alpha,\ i.e.\ \beta^* = -log\ (\log(1-\alpha))$ where α is set to 0.01 following Bjursell et al. (2017).

Building on the evidence that expected stock return is a function of average jump size or intensity (Christoffersen et al., 2012), we focus on the size and intensity of jumps. Jump size is measured in terms of price returns and jump intensity is the ratio of the number of 5-minute jumps detected per day to the total number of 5-minute intervals during the trading day. We observe in Panel A in Table 1 that negative jumps generally occur more frequently than positive jumps, while positive jumps tend to be smaller in size and intensity. Interestingly, the average size and intensity of jumps prior to the 2016 Paris climate agreement is approximately 1.3 and 1.2 times, respectively, compared to the post Paris agreement period, suggesting that the climate agreement has had a stabilising effect on jump behaviour in green equities. Finally, the descriptive statistics for the climate factors presented in Panel B highlight the media attention on the discussions, announcements and political appointments that affect climate related policies throughout the sample period, captured by the climate policy factor.

Table 1: Descriptive statistics

Panel A: Intraday Jumps			
	Whole sample	Pre-Paris agreement	Post-Paris agreement
Number of Jumps	5,183	4,683	500
(+) Jumps	2,534	2,303	231
(–) Jumps	2,649	2,380	269
Jump Intensity	0.034	0.036	0.027
(+) Jumps	0.016	0.018	0.011
(–) Jumps	0.017	0.018	0.013
Jump Size	0.318	0.327	0.267
(+) Jumps	0.315	0.321	0.271
(–) Jumps	-0.322	-0.331	-0.261

Panel B: Climate Risk Proxies				
	Mean	Std.	Min	Max
Climate Policy	0.740	1.031	0.000	10.856
International Summit	0.477	0.799	0.000	11.959
Global Warming	0.383	0.600	0.000	9.218
Natural Disaster	0.286	0.508	0.000	5.195

Notes: Panel A reports the descriptive statistics of 5-minute price jumps for the Invesco Global Clean Energy ETF, obtained from intraday returns over the Jun 2007 – Nov 2019 period. Jump test statistic is computed following Lee and Mykland (2008). Jump size is the corresponding return when a jump is identified by the jump statistic. Jump intensity is the ratio of the number of 5-minute jumps detected per day to the total number of 5-minute intervals during the trading day (9:30 – 4 pm). 2016 is used as the cutoff year when the Paris Agreement was signed. Panel B reports the descriptive statistics for daily climate risk proxies, namely climate policy, international summits, global warming and natural disasters.

2.1 Methodology

In order to explore the dynamic predictive relationship between climate risk and jumps, we begin our analysis by examining time-varying causality running from each climate measure via the framework of Shi et al. (2020). Let y_t be a k-vector time series of jump measures generated by the process $y_t = y_0 + \alpha y_1 t + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t$. The Granger causality test for a possible integrated variable y_t is conducted via a lag augmented VAR suggested by Dolado and Lütkepohl (1996) in the form.

$$Y = \tau\Gamma' + X\Theta' + B\Phi' + \varepsilon \, , \tag{2}$$

where $Y = (y_1, \ldots, y_T)_{T*n'}, \tau = (\tau_1, \ldots, \tau_T)_{t*2'}, \tau_t = (1, t)_{2*1'}, X = (x_1, \ldots x_T)_{T*np'}, x_t = (y_{t-1'}, \ldots, y_{t-p'})_{np*1'}$ $\Theta = (\beta_1, \ldots, \beta_p)_{n*np}, B = (b_1, \ldots, b_T)_{T*nd'}, b_t = (y_{t-p-1'}, \ldots, y_{t-p-d'})_{nd*1'}, \Phi = (\beta_{p+1}, \ldots, \beta_{p+d})_{n*nd}$ and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_T)_{T*n'}$ and d is the maximum order of integration for y_t. The test employs the Wald statistic over [f_1, f_2] with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$, formulated as $SW_f(f_0) = \underset{(f_1,f_2)\in\Lambda_0, f_2=f}{sup}\{W_{f_2}(f_1)\}$, where $\Lambda_0 = \{(f_1, f_2): 0 < f_0 + f_1 \leq 1 \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for some minimal sample size $f_0 \in (0,1)$ in the regressions. In our application, following Shi et al. (2020), we employ the recursive evolving window algorithm as the most reliable approach to detect causality.

In addition to time-varying causality analysis, we also adopt a direct approach to examine the in- and out-of-sample predictive relationships. In-sample predictability is assessed via

$$y_{t+1} = \alpha_0 + \alpha_1 y_t + \alpha_2 cp_t + \alpha_3 is_t + \alpha_4 gb_t + \alpha_5 nd_t + \varepsilon_t \tag{3}$$

where y_{t+1} is the respective jump statistic (size and intensity) on day *t+1* and *cp*, *is*, *gb*, and *nd* are the lagged climate risk proxies associated with climate policy, international summits, global warming and natural disasters, respectively. A similar approach is also used to assess out-of-sample predictability by comparing forecasting models that include each climate predictor against the benchmark model that excludes them. To evaluate the forecasts of competing models, we adopt the model confidence set (MCS) methodology of Hansen et al. (2011) wherein we rank the models based on three loss functions, $MSE = N^{-1}\sum_{t=1}^{N}(J_t - \hat{J}_t)^2$, $HMSE = N^{-1}\sum_{t=1}^{N}(1 - \frac{\hat{J}_t}{J_t})^2$ and $HMAE = N^{-1}\sum_{t=1}^{N}|1 - \frac{\hat{J}_t}{J_t}|$, where $\hat{J}_t$ denotes the out-of-sample jump forecast obtained from the respective model and N is the length of out-of-sample evaluation period[1]. This approach has been widely applied in the literature to evaluate the out-of-sample prediction performance of volatility models (e.g. Bauwens and Otranto, 2016; Koopman et al., 2016; Niu et al., 2023). Following the literature, we select the range-based (Range) and semi-quadratic (SemiQ) statistics as the MCS statistics and compute their p-values using a bootstrap program. The Range and SemiQ statistics are formulated as:

$$T_R = \underset{u,v\,\epsilon\, M}{\text{MAX}} \frac{|\bar{d}_{i,uv}|}{\sqrt{var(d_{i,uv})}},\ T_{SQ} = \underset{u,v\,\epsilon\, M}{\text{MAX}} \frac{(\bar{d}_{i,uv})^2}{var(\bar{d}_{i,uv})},\ \bar{d}_{i,uv} = n^{-1}\sum_{t=1}^{n}\bar{d}_{i,uv}, t \tag{4}$$

where $\bar{d}_{i,uv}$ is the relative sample loss statistic which measures the relative sample loss between the i^{th} and j^{th} models. Given that each model has a p-value in an initial set of competing models, the MCS test selects models with superior predictive performance based on the criterion of p-values greater than 0.10.

[1] MSE, HMSE and HMAE denote the mean squared-error, heteroskedasticity-adjusted MSE and mean absolute error (MAE), respectively.

3. Empirical results

Figures 1 and 2 plot the results of causality running from each climate risk measure to jump size and intensity, respectively. Note that the daily climate measures reflect the intensity of news coverage for climate-related events. While the natural disasters and global warming factors capture the occurrence of natural disasters and the rise in temperatures driven by rising emissions, respectively, the international summits and climate policy factors capture international events and policy related discussions related to climate change, respectively. We observe significant causality running from all climate risk proxies to jump size in Figure 1. International summits along with natural disasters have a particularly strong causal effect on jump size as well as its positive and negative variations in Figures A1 and A2 in the Appendix.

We observe in Figure 1 a significant rise in causal effects on both jump measures in late 2009 following the publication of the climate report by the U.N. Panel on Climate Change (December 2009). This period also coincides with BP oil spill in the Gulf of Mexico (April 2010) which is highlighted by a rise in causality from natural disasters to jump size in particular. The predictive power of international summits and natural disasters could be explained by the bad news they capture regarding new regulations on pollutants and rising public attention to climate events, respectively. The causal effect of international summits on positive jump size in Figure A1 is particularly evident starting with late 2012 when the U.S. climate extremes index doubled and 50% of U.S. counties were named as disaster areas[2]. Considering that international summits mostly relate to the introduction of a global tax on pollution, we argue that bad news that relate to brown industries serve as a driver of positive jumps in green assets.

A similar predictive pattern is also observed for jump intensity in Figure 2 where international summits are found to have a consistent causal effect on the intensity of jumps in both directions (Figures A3 and A4). In the case of global warming, Faccini et al. (2023) observe that this factor can be related to less often to a significant event. In our case, we observe a significant rise in causality running from global warming to jump size in particular during mid to late 2009 which again coincides with the publication of the climate report by the U.N Panel on Climate Change. The causal effects of global warming on the intensity of jumps, however, is found to be largely insignificant. Overall, our finding show that strong causal effects are present driven particularly from measures of transition climate risks to both jump measure, in line with the recent evidence by Faccini et al. (2023) that transition climate risk is a dominant driver of stock returns as investors price the risk of government intervention in their trades of these assets. From an investment perspective, considering the evidence that jumps serve as a systematic risk factor in expected stock returns (Dunham and Friesen, 2007), our findings suggest the presence of a climate policy related risk premium in stock returns through its effect on jump dynamics.

[2] https://www.wri.org/insights/look-back-2012-year-extreme-weather-events

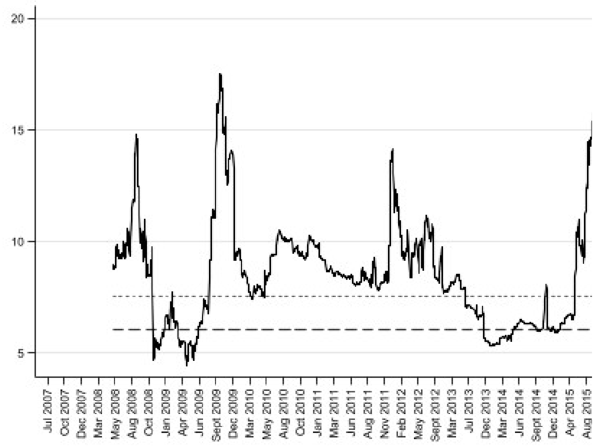
Figure 1: Time varying causality between climate risk and jump size in green assets.

Jump Size

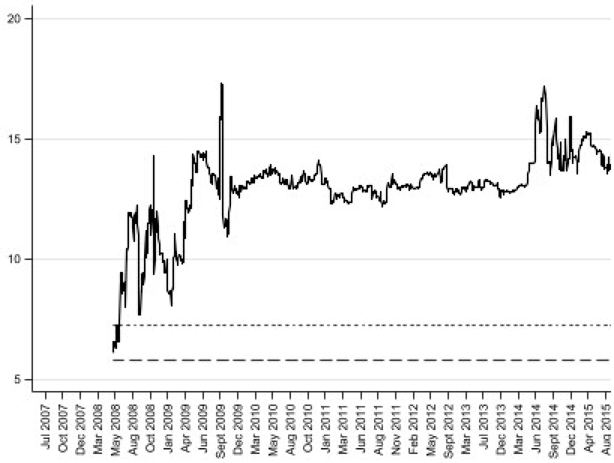
Climate Policy

International Summits

Global Warming



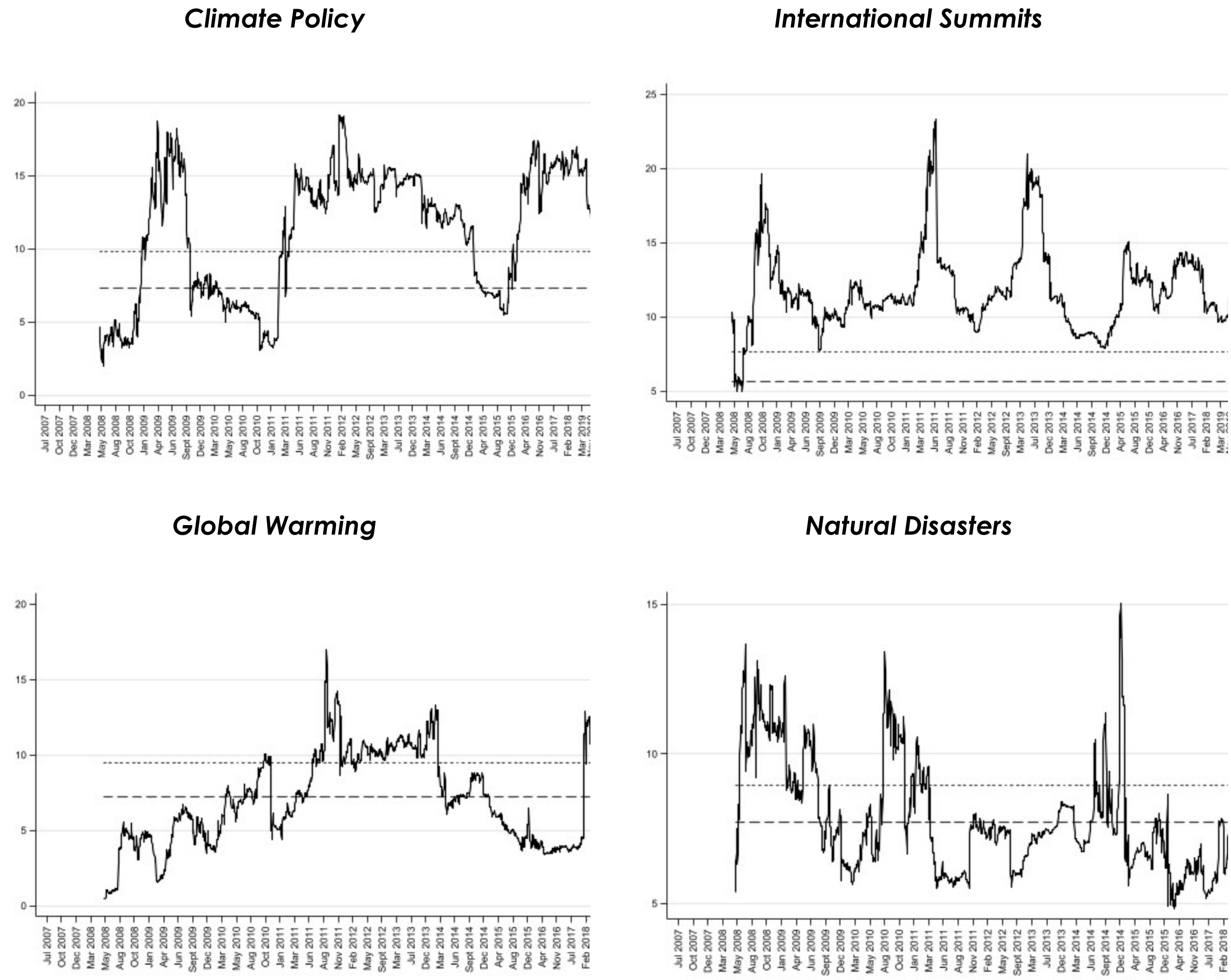
Natural Disasters



Notes: This figure presents the recursive expanding Wald test statistics (in the y-axis) for Granger-causality from each climate uncertainty measure to jump size. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

Figure 2: Time varying causality between climate risk and *jump intensity* in green assets.

Jump Intensity



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

The in-sample predictability results reported in Table 2 further support the predictive power of transition risks over both the jump size and intensity. We find that greater climate policy and international summits factors predict higher jump size and intensity, while they negatively predict the occurrence of negative jumps. Considering that an increase in the international summits factor signals bad news for the economy as the main implication of these meetings is a possible global tax on pollutants, this means that bad news for the economy in transition drives the intensity and size of positive jumps in green assets. Although a rise in the climate policy factor can signal good or bad news for investors depending on the political tendency of the governing party, our findings show that increased uncertainty surrounding policy actions also drives jump dynamics in green stocks.

Table 2: In-sample predictability of jumps

	Jump Size	Positive Jump Size	Negative Jump Size	Jump Intensity	Positive Jump Intensity	Negative Jump Intensity
α_0	0.00277***	0.00279***	-0.00287***	0.03100***	0.02140***	0.02200***
	(0.00009)	(0.00011)	(0.00014)	(0.00072)	(0.00058)	(0.00060)
Climate Policy	0.00022***	0.00026***	-0.00017**	0.00160***	0.00082**	0.00031
	(0.00005)	(0.00006)	(0.00007)	(0.00041)	(0.00032)	(0.00032)
International Summit	0.00039***	0.00030***	-0.00038***	0.00190***	0.00010	0.00080
	(0.00008)	(0.00010)	(0.00012)	(0.00066)	(0.00050)	(0.00053)
Global Warming	-0.00008	-0.00019	-0.00003	0.00090	-0.00040	0.00080
	(0.00010)	(0.00012)	(0.00015)	(0.00082)	(0.00062)	(0.00069)
Natural Disaster	0.00008	0.00020	-0.00014	0.00050	0.00120	0.00040
	(0.00011)	(0.00015)	(0.00017)	(0.00096)	(0.00076)	(0.00077)

Notes: This table presents the results for $y_{t+1} = \alpha_0 + \alpha_1 y_t + \alpha_2 cp_t + \alpha_3 is_t + \alpha_4 gb_t + \alpha_5 nd_t + \varepsilon_t$ where y_{t+1} refers to the respective jump measure (in each column) on day t+1 and cp, is, gb, and nd are the lagged climate risk proxies for climate policy, international summits, global warming and natural disasters, respectively. Standard errors are reported in parentheses. ***,**,* represent significance at 10, 5 and 1 percent, respectively.

Further extending our analysis to out-of-sample predictability, we find in Table 3 that the predictive power of climate policy and international summits extends to out-of-sample as well. The results show that climate policy and international summits provide the most accurate out-of-sample performance to predict the size of jumps. While international summits provide greater predictive contribution for positive jumps as they signal bad news for brown industries, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies due to the information content they capture regarding regulation changes. In the case of jump intensity, we find that climate proxies show out-of-sample performance for the signed components only with climate policy as the most dominant predictor of positive jump intensity as it captures bad news for brown industries with respect to taxation of pollutants. Natural disasters also stand out over positive jump intensity forecasts, likely as an increase in this factor signals greater concern by the public and bad news for the economy overall. In contrast, both climate policy and international summits stand out with the best out-of-sample predictive performance for negative jump intensity. Overall, our findings show that transition climate risk measures, captured by the markets' concerns regarding climate policy and international summits, possess significant predictive information regarding the size and direction of price jumps, both in- and out-of-sample.[3]

[3] Based on a comment from an anonymous reviewer, we replicated our analysis for another green ETF, namely the First Trust Nasdaq Clean Edge Green Energy Index Fund, and observed similar results confirming the predictive role of transition climate factors on jumps. Likewise, controlling for market volatility in the models yields qualitatively similar inferences (available upon request).

Table 3: Out-of-sample predictability of jumps

	Range-based (Range) MCS statistic			Semi-quadratic (SemiQ) MCS		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
			Jump Size			
Benchmark	**0.20780**	0.00000	0.00000	**0.28060**	0.00000	0.00000
Climate Policy	**0.31320**	0.00000	0.00120	**0.43060**	0.00000	**0.00100**
International Summit	**1.00000**	**0.11340**	**0.28940**	**1.00000**	**0.11340**	**0.28940**
Global Warming	**0.04220**	0.00000	0.00000	**0.14440**	0.00000	0.00000
Natural Disaster	**0.04220**	0.00000	0.00020	**0.11220**	0.00000	0.00000
			Positive Jump Size			
Benchmark	0.01220	0.00000	0.00000	0.00840	0.00000	0.00000
Climate Policy	**0.17200**	0.00000	0.00060	**0.22320**	0.00000	**0.00120**
International Summit	**0.31300**	0.00960	0.05500	**0.31300**	0.00960	0.05500
Global Warming	0.07740	0.00000	0.00000	0.06200	0.00000	0.00020
Natural Disaster	0.01600	0.00000	0.00000	0.01120	0.00000	0.00020
			Negative Jump Size			
Benchmark	**0.16940**	0.00000	0.00000	**0.28820**	0.00000	0.00000
Climate Policy	**0.95100**	0.00260	**0.60400**	**0.94400**	0.00220	**0.60400**
International Summit	**0.95100**	0.00260	**0.48300**	**0.94400**	0.00140	**0.38220**
Global Warming	**0.10000**	0.00000	0.00000	**0.14080**	0.00000	0.00160
Natural Disaster	**0.16940**	0.00000	0.01820	**0.21520**	0.00020	0.01620
			Jump Intensity			
Benchmark	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Climate Policy	0.04640	0.00000	0.00000	0.05180	0.00020	0.00080
International Summit	0.04640	0.00700	0.01520	0.05180	0.00700	0.01520
Global Warming	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Natural Disaster	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
			Positive Jump Intensity			
Benchmark	0.00880	0.00000	0.00000	0.09640	0.00000	0.00000
Climate Policy	**1.00000**	**1.00000**	**1.00000**	**1.00000**	**1.00000**	**1.00000**
International Summit	**0.22220**	0.00060	0.00020	**0.41720**	0.02740	0.00560
Global Warming	0.00880	0.00000	0.00000	0.04380	0.00000	0.00000
Natural Disaster	**0.57100**	**0.17720**	**0.10020**	**0.57000**	**0.15700**	0.10360
			Negative Jump Intensity			
Benchmark	0.00040	0.00000	0.00000	0.00080	0.00000	0.0000
Climate Policy	**0.83620**	**0.27600**	**0.16780**	**0.83620**	**0.23300**	**0.1226**
International Summit	**0.39060**	**0.27600**	**0.16780**	**0.32020**	**0.23180**	**0.1206**
Global Warming	0.00820	0.00020	0.00000	**0.02180**	0.00300	0.0006
Natural Disaster	0.00040	0.00000	0.00000	0.00360	0.00000	0.0000

Notes: This table presents the model confidence set (MCS) p-values based on the range-based (Range) and semi-quadratic (SemiQ) test statistics, T_R and T_{SQ}. In each panel, the benchmark model that excludes the climate predictors (represented in shaded rows) is tested against the extended models that incorporate each climate risk proxy, respectively. MSE, HMSE and HMAE denote the mean squared-error, heteroskedasticity-adjusted MSE and mean absolute error (MAE), respectively. Models with p>0.10 are indicated in bold. We follow a 75% in-sample and 25% out-of-sample split.

4. Conclusion

This paper shows that climate risk can help predict the size and direction of intraday jumps in green assets, both in and out-of-sample. Transition climate risk proxies including international summits and climate policy are found to be the most dominant predictors compared to proxies of physical climate risks. While international summits that capture bad news for brown industries regarding the taxation of pollutants provide the greatest predictive contribution for positive jumps in green assets, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies. Our findings provide novel insight to the role of climate risk as a driver of idiosyncratic tail risk and jump innovations in green assets and imply that asset pricing models that incorporate jump risk as a risk factor can be improved by exploiting the predictive relationship between jumps and climate risk. The results pave the way for pricing models in green equities that incorporate jump risk as a function of climate risk.

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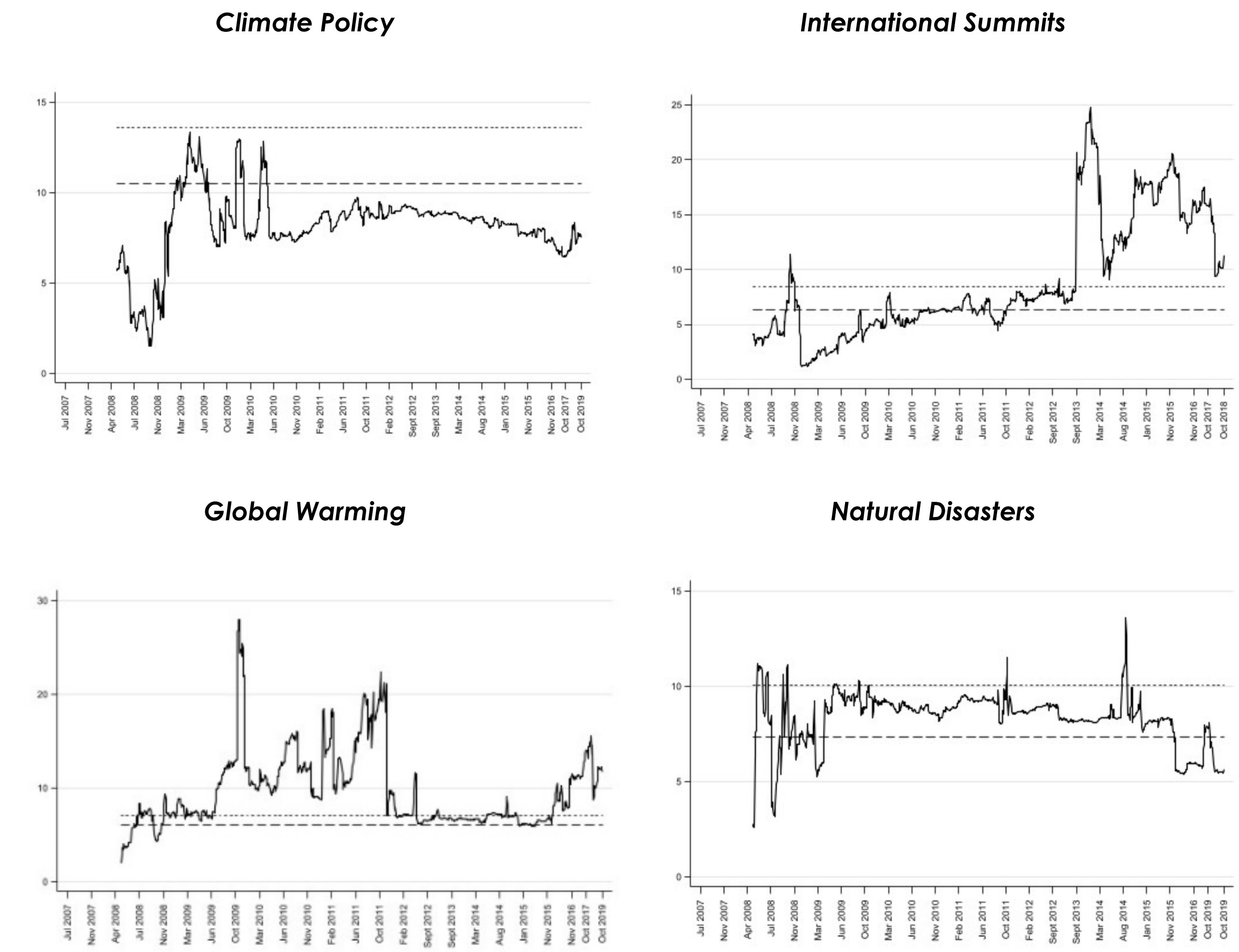
Appendix

Figure A1: Time varying causality between climate risk and *positive jump size*.

Positive Jump Size

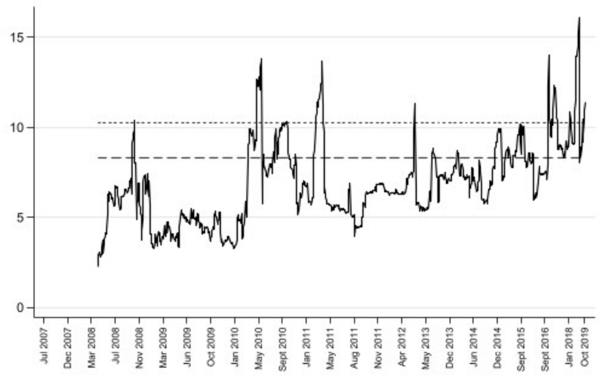


Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *positive jump size*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

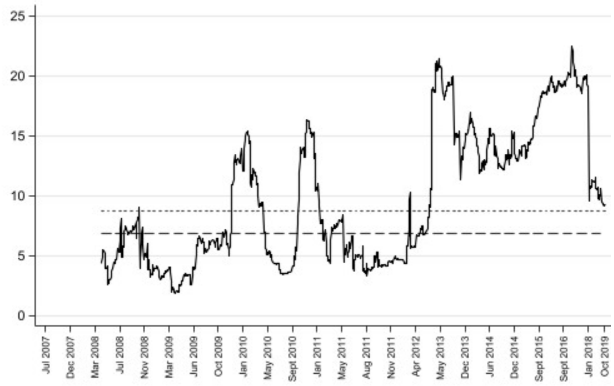
Figure A2: Time varying causality between climate risk and *negative jump size*.

Negative Jump Size

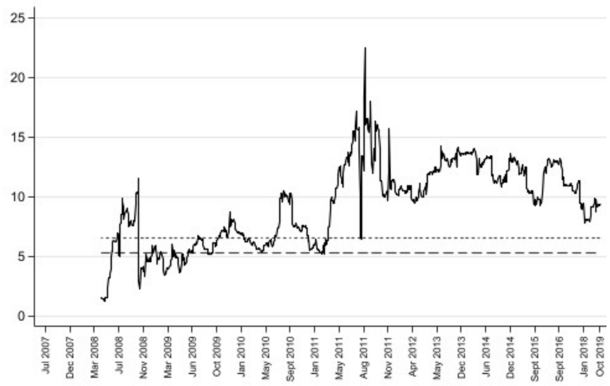
Climate Policy



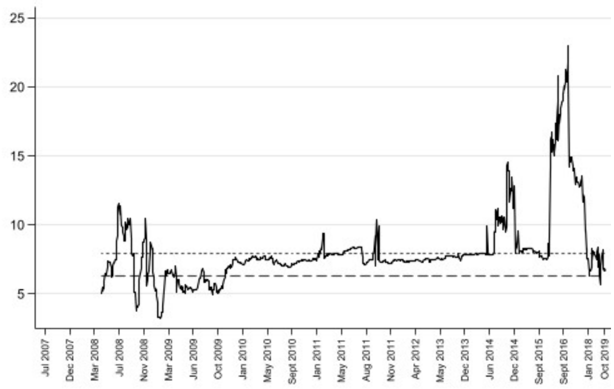
International Summits



Global Warming



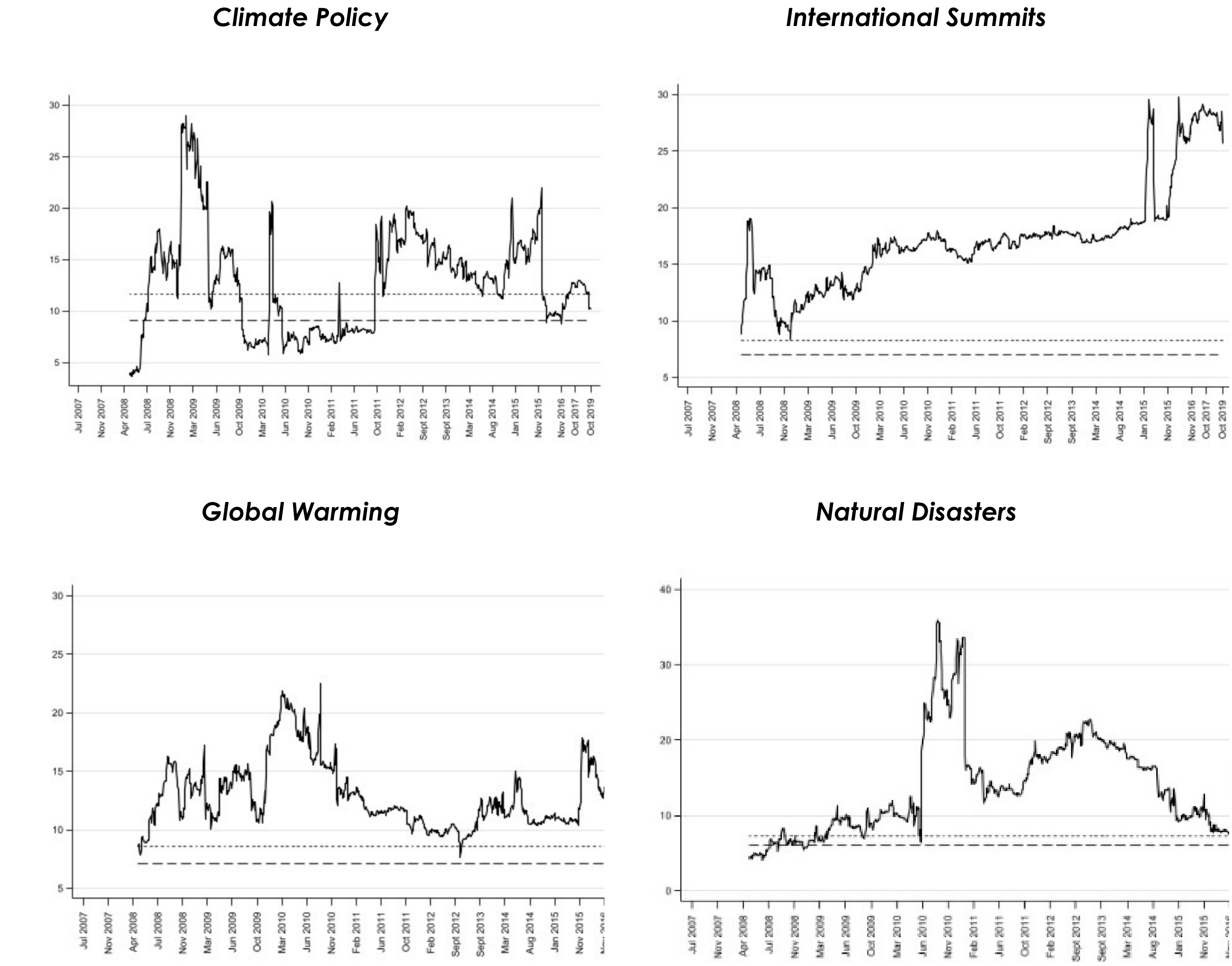
Natural Disasters



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *negative jump size*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

Figure A3: Time varying causality between climate risk and *positive jump intensity*.

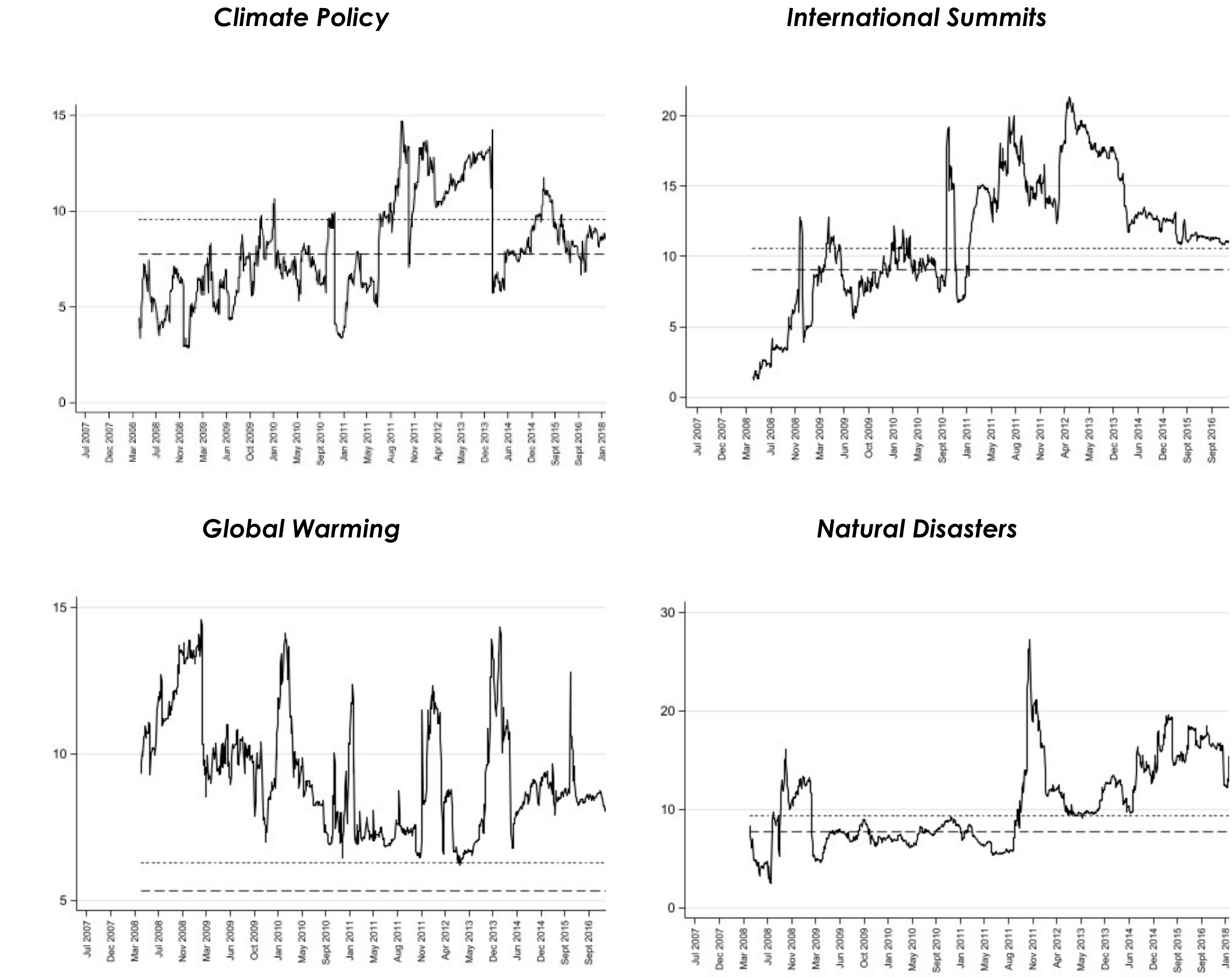
Positive Jump Intensity



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *positive jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

Figure A4: Time varying causality between climate risk and *negative jump intensity*.

Negative Jump Intensity



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *negative jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.