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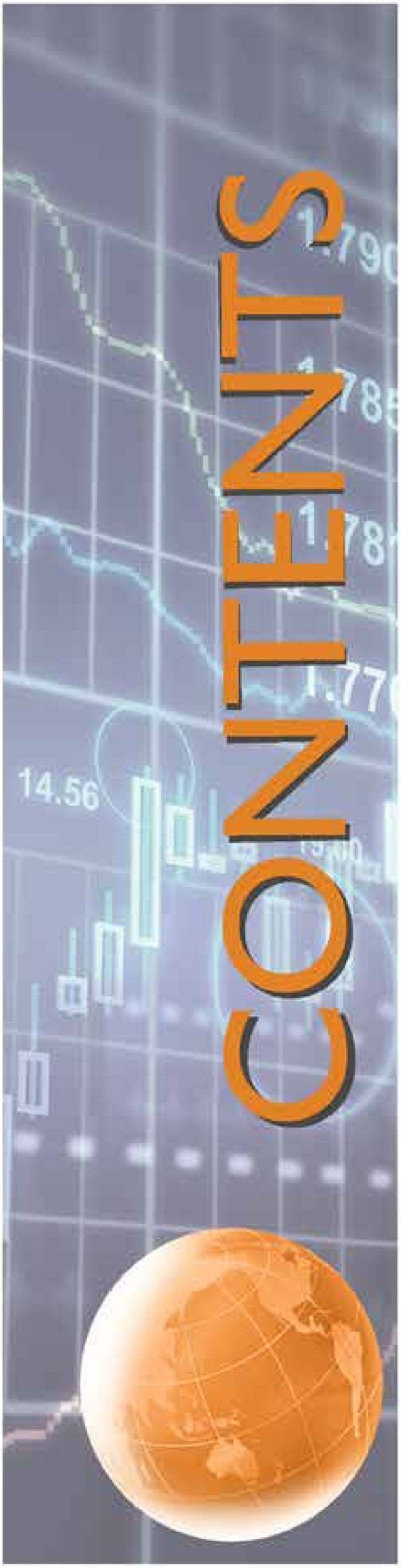

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THE JANUARY ANOMALY AND ANOMALIES IN JANUARY

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Abstract

Prior research finds that stocks earn significantly higher returns in January compared to other months, with the effect most often attributed to tax-motivated selloffs in December leading to price reversion in January. We examine how patterns in turn-of-the-year performance impact prominent return anomalies. We find that short-term reversals strengthen while momentum changes sign at the turn of the year, and such patterns are more pronounced following years of recession and poor market performance, consistent with tax-loss selling playing a key role. Although additional factors are likely to contribute to the overall effect, no significant change in anomaly performance occurs midyear, casting doubt on window dressing as a primary driving force.

Keywords: January effect, market efficiency, stock market anomalies, tax-loss selling

JEL Codes: G10, G14

1. Introduction

A large body of literature documents significantly higher abnormal stock returns in January, with researchers offering several possible explanations. The "January effect" is most frequently attributed to tax-motivated selloffs in December leading to price reversion in January (see, e.g., Chen and Singal, 2004; D'Mello et al., 2003; Gultekin & Gultekin, 1983; Ligon, 1997; Schultz, 1985). Yet, other studies suggest additional factors may play a significant role, such as institutional window dressing (Kang, 2010; Ng & Wang, 2004), market microstructure (Bhardwaj & Brooks, 1992; Griffiths & White, 1993), or some combination of factors (Berges et al., 1984; Dyl & Maberly, 1992; Haug & Hirschey, 2006). While our evidence is most consistent with a tax-loss harvesting explanation, we focus primarily on the impact of return seasonality on prominent investing styles and anomaly-based strategies.

The January effect is characterized by strong January returns to stocks with poor prior-year performance, and the investment holdings for several of the most well-known anomaly portfolios are also heavily influenced by past performance. For example, momentum strategies buy companies with strong prior year returns and short or avoid firms with poor past returns. Despite the strong empirical support for return momentum (Jegadeesh & Titman, 1993), such strategies run counter to the January effect, which predicts that past loser stocks will outperform in January. By contrast, value strategies invest in stocks with high book-to-market ratios that are likely to have experienced poor prior-year returns on average and whose performance may be augmented by any January rebound. Thus, we aim to address an open question: whether common anomaly strategies maintain their profitability throughout the year or exhibit significant return seasonality.

We explore the January effect's impact on many of the most prevalent anomaly investment strategies, including return-based anomalies whose performance is directly related to year-end tax considerations, such as momentum and short-term reversal, as well as other prominent anomalies, including size, value, profitability, and investment. Our work is most closely related to prior studies documenting the January effect's concentration among certain stocks. For instance, several prior studies find higher January returns to small-cap stocks with gains concentrated at the start of the month (e.g., Berges et al., 1984; Haug & Hirschey, 2006; Roll, 1983; Thaler, 1987). Additionally, Chou et al. (2011) provide evidence that large-cap stocks only earn a value premium in January, while Mashruwala and Mashruwala (2011) find that high-accruals quality stocks outperform low-accruals quality stocks in January but underperform in other months. The findings of Haug and Hirschey (2006) are particularly relevant to our study, as they show a strong and persistent pattern in the size, value, and momentum factor returns in January.

Our paper makes two main contributions to this literature. First, we use both time series and cross-sectional tests to show that while some anomalies are more pronounced during January, such as investment and short-term return reversals, others, such as size, profitability, and momentum change signs for January relative to all other months. Our time series portfolio-level tests measure the abnormal returns to the top, bottom, and long-short anomaly decile portfolios in January and all other months. Our stock-level tests allow us to assess the marginal effect of each anomaly variable while controlling for the others. Second, we perform subsample analyses to shed additional light on the driving force of the January effect's impact on anomaly performance. Notably, while small-cap stocks exhibit significant January abnormal returns across all subsamples, momentum experiences more significant losses, and short-term reversals have more significant gains following recessions and years with below-median stock market performance. Although this does not rule out the possibility of other factors playing an important contributing role, such evidence is consistent with the year-end tax-loss selling explanation and highlights that the January effect is most pronounced following market downturns when many stocks end the year with significant losses.

The rest of the paper is organized as follows. Section 2 describes our dataset, anomaly variables, and methodology; Section 3 reports the results of our empirical tests; and Section 4 concludes.

2. Data and methodology

2.1 Anomaly variables and summary statistics

The anomalies literature contains a growing number of proposed return predictors, yet data mining concerns and lack of out-of-sample replicability cast doubt on the usefulness of many variables (Harvey et al., 2016; Hou et al., 2020). Thus, we limit our focus to a set of predictors that have withstood years of academic scrutiny and remain ubiquitous across the finance literature. Specifically, we include the characteristics for size, value, profitability, and investment that are used to capture patterns in average stock returns in Fama and French (2015). We then add momentum (Asness et al., 2013; Jegadeesh & Titman, 1993; Jegadeesh and Titman, 2001) and short-term reversal (Jegadeesh, 1990; Lehmann, 1990) given their prevalence and ability to capture prior-year return performance, and we winsorize all anomaly variables at their respective 1st and 99th percentiles to limit the influence of outliers. The outcome variable throughout our analyses, EXRET, is defined as the monthly stock return minus the risk-free rate, and we define a time-series variable, JAN, which is set equal to one for observations in the month of January and zero for all other months. Table 1 provides variable definitions.

Our sample period spans from January 1981 to December 2020, and we combine data from CRSP and Compustat to construct our variables. Following prior studies, we match accounting data from fiscal year-end financials in year t-1 with returns from July of year t through June of year t+1 to prevent potential look-ahead bias. We then retain only common equity securities (share codes 10 and 11) for firms traded on NYSE, NASDAQ, or AMEX, and we remove financial firms (SIC codes 6000 to 6999), utility companies (SIC codes 4900 to 4999), and firms with share prices below $1.

Table 1: Variable Definitions

SIZE	Natural log of shares outstanding (SHROUT) times the share price (PRC)
BM	Natural log of the book value of common equity divided by the market value of common equity, where market value equals SHROUT times PRC
ROE	Net income (NI) divided by the book value of equity
INV	Total asset growth from year *t-1* to year *t*, defined as the change in the Compustat total assets variable (AT) scaled by its lagged value
MOM	Cumulative stock return from month *t-12* to *t-2* relative to the period of performance measurement
REV	Stock return (RET) in month *t-1* relative to the period of performance measurement
EXRET	Investment return in excess of the monthly risk-free rate (in percent)
JAN	Indicator variable equal to one if the investment return is measured in January and zero otherwise

Table 2 provides summary statistics for our key variables of interest. Because we winsorize the anomaly variables, the values for the 1st and 99th percentiles reflect the minimums and maximums for each anomaly variable, respectively. The only variables that are not winsorized are EXRET, which represents our dependent variable that captures the actual stock performance in excess of the risk-free rate, and the indicator variable JAN which has a mean value close to one-twelfth by construction. Our full sample's average monthly excess return is 0.726% but with considerable variation at the individual stock level.

Table 2: Summary Statistics

Variable	Mean	Median	Stdev	P1	P5	P95	P99
SIZE	12.401	12.235	2.011	8.507	9.369	16.022	17.651
BM	-7.734	-7.669	0.961	-10.581	-9.463	-6.250	-5.531
ROE	-0.028	0.084	0.561	-3.314	-0.874	0.350	1.813
INV	0.165	0.071	0.421	-0.473	-0.242	0.898	2.512
MOM	0.141	0.066	0.550	-0.789	-0.574	1.130	2.632
REV	0.012	0.003	0.147	-0.385	-0.216	0.263	0.563
EXRET	0.726	-0.009	16.78	-39.65	-22.36	24.99	52.00
JAN	0.086	0.000	0.281	0.000	0.000	1.000	1.000

Note: This table presents summary statistics for our primary variables of interest over the sample period from January 1981 to December 2020. Statistics are reported at the individual stock/company level and include the mean, median, standard deviation, 1st percentile, 5th percentile, 95th percentile, and 99th percentile. All anomaly variables are winsorized at their 1st and 99th percentiles, and only EXRET is reported in percent per month.

2.2 Methodology

To test whether each anomaly exhibits a January seasonality, we first conduct univariate portfolio sorts by dividing all publicly traded firms into deciles by the values of each of our anomaly variables: size (*SIZE*), book-to-market (*BM*), profitability (*ROE*), investment (*INV*), momentum (*MOM*), and short-term reversal (*REV*). Fama French three-factor model alphas to long-short portfolios that buy stocks in the top decile and short stocks in the bottom decile are then used to measure whether a given variable produces an abnormal return. We conduct this analysis separately for the full sample, January months only, and all non-January months only, and we repeat the tests using both value-weighted and equal-weighted portfolios to confirm robustness. Our primary focus is on how each anomaly strategy's abnormal returns vary across the year, as reflected by the alphas (α_i) from Equation 1.

$$EXRET_{i,t} = \alpha_i + b_i MKTRF_t + c_i SMB_t + d_i HML_t + \varepsilon_{i,t} \quad (1)$$

Our second set of tests is performed at the individual stock level, and we test for differential January performance using both cross-sectional and panel regressions. These analyses measure the incremental contribution of each anomaly variable while allowing for different January and non-January coefficients and controlling for other return predictors. In the cross-sectional analysis, we estimate Fama and MacBeth (1973) regressions as shown below in Equation 2,

$$EXRET_{i,t+1} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 BM_{i,t} + \beta_3 ROE_{i,t} + \beta_4 INV_{i,t} + \beta_5 MOM_{i,t} + \beta_6 REV_{i,t} + e_{i,t+1} \quad (2)$$

where the regression is estimated separately for all January and non-January months. This allows us to evaluate the average marginal effect of each variable and observe whether there is a change in the sign and strength of its association with future returns.

To test for significant differences between each variable's January and non-January coefficient, we estimate a panel regression that includes an interaction term for each anomaly variable multiplied by the January indicator, *JAN*. We include time-fixed effects to control for period-specific factors that influence the returns of all stocks and use two-way clustered standard errors by firm and month to account for potential residual correlation. Equation 3 presents our panel regression which includes the six anomaly variables and six interaction terms.

$$EXRET_{i,t+1} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 SIZE_{i,t} * JAN_{i,t+1} + \beta_3 BM_{i,t} + \beta_4 BM_{i,t} * JAN_{i,t+1} + \beta_5 ROE_{i,t} + \beta_6 ROE_{i,t} * JAN_{i,t+1} + \beta_7 INV_{i,t} + \beta_8 INV_{i,t} * JAN_{i,t+1} + \beta_9 MOM_{i,t} + \beta_{10} MOM_{i,t} * JAN_{i,t+1} + \beta_{11} REV_{i,t} + \beta_{12} REV_{i,t} * JAN_{i,t+1} + \mu_{t+1} + e_{i,t+1} \quad (3)$$

Our primary focus is on the six interaction coefficients, which capture whether each variable has a significantly different association with future returns in January compared to other months. If year-end tax-loss selling and other correlated factors play a key role, then we expect a negative β_{10} indicating an attenuation or reversal of momentum and a negative β_{12} implying a stronger short-term reversal effect in January. We also predict a negative β_2, since prior studies find that the January rebound is concentrated among more volatile small-cap stocks in earlier sample periods (Haug & Hirschey, 2006; Keim, 1983). Last, although their effects are less directly impacted by prior return performance, we expect a positive interaction for value (β_4), negative interaction for profitability (β_6), and the sign of the investment interaction is ambiguous (β_8).

3. Empirical Results

Table 3 presents the results from our univariate portfolio sorts on the individual anomaly variables, with Panel A reporting value-weighted 3-factor alphas and Panel B reporting equal-weighted 3-factor alphas. Focusing first on the value-weighted tests, we find several meaningful differences between the January and non-January subsamples. For instance, although size has an insignificant return spread overall, it yields a highly significant negative alpha of -5.945% (t = -9.98) in Januarys but a significant positive alpha across the remainder of the year of 0.616% (t = 3.87). Such evidence highlights the continued outperformance of small-cap stocks during January (Haug & Hirschey, 2006; Roll, 1983) and documents large-cap outperformance in non-January months. The book-to-market long-short portfolio also yields a small and insignificant alpha across the full sample, but its abnormal returns are not statistically significant within the January and non-January subsamples. Although we expected high book-to-market ratio stocks to outperform in January, given potentially greater tax-loss selling incentives and prior evidence of strong January returns to the value factor (Haug & Hirschey, 2006), there are two primary explanations for the lack of significant alpha. First, several studies document much lower value premiums in recent decades, so there may be less of a return spread between value and growth stocks during our sample period compared to earlier periods (Fama & French, 2021; Linnainmaa & Roberts, 2018). Second, because we report Fama-French (1993) three-factor model alphas, the smaller alphas also reflect that the HML factor is relatively successful in explaining the returns to the book-to-market decile portfolios.[1]

Table 3: Anomalies in January versus Non-January Months

Panel A: Value-weighted 3-factor alphas										
Portfolio:	**D1**	**D10**	**D10-D1**	**D1**	**D10**	**D10-D1**	**D1**	**D10**	**D10-D1**	**Long – Short**
	All Months			**January Only**			**Non-January Months**			
Size (SIZE)	0.000	0.025*	0.025	5.955***	0.010	-5.945***	-0.587***	0.029**	0.616***	Big – Small
	(0.00)	(1.87)	(0.14)	(9.76)	(0.18)	(-9.98)	(-3.79)	(2.06)	(3.87)	
Book-to-Market (BM)	0.142	-0.082	-0.224	-0.240	1.390	1.630	0.185**	-0.251	-0.436*	Value – Growth
	(1.62)	(-0.42)	(-0.98)	(-0.72)	(1.68)	(1.59)	(2.06)	(-1.29)	(-1.93)	
Profitability (ROE)	-0.115	0.216***	0.331*	1.800***	-0.123	-1.922***	-0.296*	0.238***	0.534***	Robust – Weak
	(-0.73)	(2.93)	(1.77)	(4.51)	(-0.45)	(-3.52)	(-1.79)	(3.12)	(2.74)	
Investment (INV)	0.077	-0.341***	-0.419**	1.129*	-0.665	-1.794**	-0.012	-0.315**	-0.304	Aggressive –
	(0.55)	(-2.93)	(-2.19)	(1.83)	(-1.42)	(-2.27)	(-0.08)	(-2.62)	(-1.55)	Conservative
Momentum (MOM)	-1.458***	0.509***	1.966***	0.423	-0.081	-0.504	-1.679***	0.590***	2.269***	Winner – Loser
	(-5.28)	(3.27)	(5.28)	(0.40)	(-0.12)	(-0.32)	(-5.94)	(3.77)	(6.06)	
ST Reversal (REV)	-0.607***	-0.182	0.425	0.625	-1.553***	-2.178**	-0.744***	-0.036	0.707**	ST Winner – Loser
	(-3.16)	(-1.00)	(1.38)	(0.87)	(-2.98)	(-2.10)	(-3.77)	(-0.19)	(2.22)	
Panel B: Equal-weighted 3-factor alphas										
	All Months			**January Only**			**Non-January Months**			
Size (SIZE)	0.242	0.009	-0.233	6.612***	-0.024	-6.636***	-0.386**	0.013	0.399**	Big – Small
	(1.26)	(0.26)	(-1.18)	(10.23)	(-0.18)	(-9.80)	(-2.28)	(0.38)	(2.27)	
Book-to-Market (BM)	-0.313***	0.315	0.628***	0.258	4.634***	4.376***	-0.369***	-0.135	0.234	Value – Growth
	(-3.37)	(1.56)	(2.81)	(0.72)	(7.43)	(5.47)	(-3.85)	(-0.69)	(1.06)	
Profitability (ROE)	-0.291	-0.127	0.164	4.611***	0.773***	-3.837***	-0.779***	-0.232***	0.547***	Robust – Weak
	(-1.58)	(-1.60)	(0.92)	(6.25)	(3.11)	(-4.75)	(-4.58)	(-2.90)	(3.25)	
Investment (INV)	0.259	-0.905***	-1.164***	4.439***	0.590	-3.849***	-0.152	-1.082***	-0.930***	Aggressive –
	(1.65)	(-7.31)	(-7.31)	(8.12)	(1.22)	(-6.36)	(-1.02)	(-8.93)	(-5.80)	Conservative
Momentum (MOM)	-1.453***	0.478***	1.932***	3.286***	1.075**	-2.211	-1.959***	0.431***	2.390***	Winner – Loser
	(-5.83)	(4.03)	(6.30)	(3.01)	(2.04)	(-1.55)	(-8.34)	(3.58)	(8.08)	
ST Reversal (REV)	0.087	-0.746***	-0.834***	4.983***	-0.790*	-5.773***	-0.419**	-0.744***	-0.325	ST Winner – Loser
	(0.45)	(-5.34)	(-3.26)	(5.04)	(-1.75)	(-4.65)	(-2.44)	(-5.04)	(-1.36)	

Note: Panel A reports value-weighted Fama-French 3-factor alphas for the highest and lowest decile portfolios ranked by each anomaly variable across all months, January only months, and non-January months. The reported values reflect that alphas in percent per month for the following regression: $EXRET_{i,t} = \alpha_i + b_i MKTRF_t + c_i SMB_t + d_i HML_t + \varepsilon_{i,t}$. Panel B repeats these tests using equal-weighted portfolio returns. *t*-statistics are reported in parentheses, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1981 to December 2020.

The profitability portfolios exhibit substantial seasonality in which the long-short alpha is significantly positive in non-January months but significantly negative in Januarys, consistent with firms that

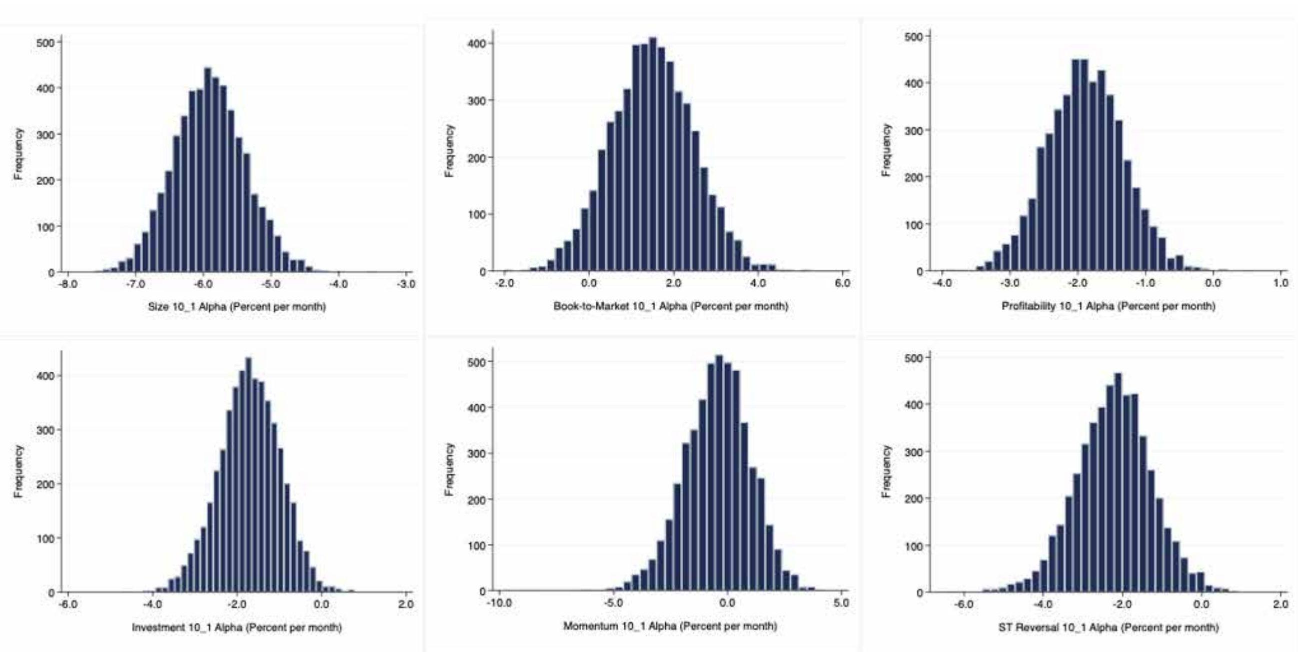
[1]In unreported results, we find the average return spread between the top and bottom book-to-market decile portfolios is 2.48% (t = 1.78) per month in January compared to only 0.06% (t = 0.20) in other months. By comparison, the reported alphas are 1.63% (t = 1.59) and -0.44% (t = -1.93) in Januarys and non-Januarys, respectively. In both instances, high return volatility also contributes to the lack of statistical significance.

struggled in the prior year being oversold late in the year before rebounding in January. By contrast, the abnormal returns to the investment long-short portfolio are negative across both subsamples, but both the magnitude and statistical significance suggest a more pronounced underperformance of high investment firms in January (-1.794%, t = -2.27) with small and insignificant abnormal returns in other months (-0.304%, t = -1.55).

Consistent with the tax explanation, we also find large seasonalities in anomalies based on past performance. While momentum generates the largest alpha across the full sample (1.966%, t = 5.28), the estimated long-short alpha is negative albeit insignificant in January (-0.504%, t = -0.32) but large and positive in Januarys (2.269%, t = 6.06). This confirms that the year-end reversal effect is sufficiently robust to counteract and prevent potential gains to momentum strategies in January. Likewise, sorts on the short-term reversal variable reveal a significant reversal effect in January, but the long-short alpha is positive in all other months, thus, reflecting return continuation rather than reversal. The equal-weighted test results produce similar findings, although the short-term reversal long-short abnormal return becomes negative and insignificant in non-January months while strengthening in January, and the book-to-market abnormal return becomes significantly positive. Overall, this evidence suggests that the January effect contributes to a large return seasonality in many of the most well-documented anomalies.

Given the smaller number of January observations, we also assess the bootstrapped distribution of *January Only* alphas to each anomaly long-short portfolio from Table 3, Panel A. Figure 1 displays the estimated alpha distributions across 5,000 bootstrap trials for each long-short portfolio. Overall, the results highlight that our findings are robust and unlikely to be driven by outliers. For instance, the value-weighted *SIZE* long-short portfolio yielded a *January Only* alpha of -5.945% in Table 3, and its monthly alpha never exceeded -3.460% across the 5,000 bootstrap replications with 5th and 95th percentile values of -6.926% and -4.837%, respectively. Similarly, the profitability, investment, and short-term reversal portfolios yield alpha estimates that appear reliably negative in January.

Figure 1: Bootstrapped January-Only Portfolio Alphas



Note: This figure illustrates the bootstrapped distribution of Fama-French 3-Factor model alphas for anomaly long-short portfolios using January only subsamples. The histograms present the frequency distribution for alpha across 5,000 trials for each long-short portfolio. The figures for Size, Book-to-market, and Profitability are shown across the top row, while Investment, Momentum, and Short-term reversal are displayed across the bottom row. Reported alphas are in percent per month.

Table 4: Cross-Sectional and Panel Regressions Exploring January Return Performance

	Dependent Variable: EXRETi,t+1			
	(1)	**(2)**	**(3)**	**(4)**
SIZEi,t	-0.755***	0.028	-0.037	0.04
	(-5.36)	(0.85)	(-0.92)	(1.04)
BMi,t	0.372*	0.274***	0.362***	0.350***
	(1.80)	(4.24)	(4.22)	(3.83)
ROEi,t	-1.949***	0.408***	0.083	0.296**
	(-4.74)	(4.19)	(0.55)	(1.98)
INVi,t	-0.846**	-0.747***	-0.845***	-0.838***
	(-2.42)	(-9.21)	(-6.96)	(-6.73)
MOMi,t	-0.800	0.820***	0.838***	0.942***
	(-1.46)	(5.85)	(4.21)	(4.61)
REVi,t	-10.644***	-2.469***	-2.433***	-1.417*
	(-7.73)	(-6.20)	(-2.84)	(-1.68)
SIZEi,t x JANi,t+1	N/A	N/A	N/A	-0.879***
				(-5.21)
BMi,t x JANi,t+1	N/A	N/A	N/A	0.028
				(0.12)
ROEi,t x JANi,t+1	N/A	N/A	N/A	-2.627***
				(-4.15)
INVi,t x JANi,t+1	N/A	N/A	N/A	-0.073
				(-0.14)
MOMi,t x JANi,t+1	N/A	N/A	N/A	-1.271*
				(-1.72)
REVi,t x JANi t+1	N/A	N/A	N/A	-11.147***
				(-3.24)
Constanti,t+1	15.029***	2.444***	N/A	N/A
	(6.57)	(3.94)		
Regression Type	Fama-MacBeth	Fama-MacBeth	Panel	Panel
Firm-months	January Only	Non-January	All	All
R-Squared	0.0637	0.0342	0.1313	0.1339
Within R-Squared	N/A	N/A	0.0021	0.0050
Number of Months	40	440	480	480
Observations	95,026	1,029,852	1,124,878	1,124,878

Note: The dependent variable is the monthly stock return in excess of the risk-free rate (*EXRET*) in month *t+1*. Specifications (1) and (2) are estimated using a series of monthly cross-sectional regressions following the Fama-MacBeth (1973) regression procedure. Specifications (3) and (4) include time fixed effects which prevents the inclusion of *JAN* as a separate independent variable due to collinearity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 subsequently presents our cross-sectional and panel regression results which are conducted at the individual stock level and allow us to measure the marginal effect of each anomaly variable while controlling for the others. Adding support to our prior results, we observe a sign change for size, profitability, and momentum in our cross-sectional tests with negative coefficients in January and positive coefficients in non-January months. The panel regression results in column (4) also corroborate this finding using interaction terms. In addition to a highly significant negative coefficient on the short-term reversal interaction variable that indicates a much stronger short-term reversal from December to January relative to other months; the size, profitability, and momentum interactions also enter with negative and significant coefficients. Such evidence adds support to the tax-loss selling explanation and indicates that several anomaly variables independently have a pronounced effect on January performance. By contrast, none of the interaction coefficients are statistically significant when we repeat our tests using a July indicator variable, thereby casting doubt on the effect being driven by window-dressing since similar incentives would exist midyear (Chen and Singal, 2004).[2]

Table 5 reports subsample test results to shed additional light on the potential drivers of the January effect's impact on anomaly performance. We repeat our value-weighted portfolio tests with only Januarys included, but we partition the sample period into expansion and recession, first half and second half, and Januarys following years of above versus below median stock market performance. We find that the *SIZE* abnormal return is negative and highly significant across all subsamples, highlighting the robustness of the turn-of-the-year effect in small-cap stocks. We also observe the greatest variation across subsamples for momentum (*MOM*) and short-term reversal (*REV*). Both long-short portfolios show a strong reversal effect following years of recession and below median market returns but are generally insignificant following years of expansion or above median market returns. Such evidence is consistent with the tax-loss harvesting explanation, as tax-loss selling incentives are likely to be present for fewer stocks and with smaller economic magnitude following years of strong economic and stock market growth. Although correlated variation in other factors cannot be ruled out as contributing to this phenomenon, our results highlight that January returns are most highly dependent on prior-year performance for return-based anomalies such as momentum and short-term reversal.

Table 5: Subsample Tests

	Average Three-Factor Model Residual in January					
Portfolio	Expansion	Recession	1st Half	2nd Half	High_MktRet	Low_MktRet
SIZE (10-1)	-6.058***	-7.440***	-6.605***	-6.064***	-7.104***	-5.565***
	(-7.87)	(-4.71)	(-7.96)	(-5.42)	(-8.35)	(-5.17)
BM (10-1)	1.320	5.902*	2.214**	2.259	1.600	2.873
	(1.25)	(1.98)	(2.14)	(1.20)	(1.26)	(1.68)
ROE (10-1)	-2.057***	-2.408	-2.684***	-1.571**	-3.009***	-1.245
	(-3.78)	(-1.47)	(-3.19)	(-2.41)	(-4.38)	(-1.59)
INV (10-1)	-0.618	-3.946*	-0.638	-1.929	-1.394	-1.173
	(-0.80)	(-2.00)	(-0.75)	(-1.54)	(-1.41)	(-1.01)
MOM (10-1)	-1.971	-6.307*	-1.260	-4.416	0.342	-6.018**
	(-1.05)	(-1.90)	(-0.96)	(-1.46)	(0.24)	(-2.14)
REV (10-1)	-2.107*	-5.106**	-1.735	-3.680**	-1.313	-4.101**
	(-1.70)	(-2.69)	(-1.33)	(-2.18)	(-0.92)	(-2.63)

Note: This table reports the average 3-factor model residual from value-weighted regressions estimated across all Januarys during our sample period from 1981 to 2020 for three sets of subsamples. We estimate $EXRET_{i,t} = \alpha_i + b_i MKTRF_t + c_i SMB_t + d_i HML_t + \varepsilon_{i,t}$ across all months and then test the average January value of $\varepsilon_{i,t}$. The value-weighted test portfolios are long the decile of stocks with the highest values of the given anomaly variable and short the decile of stocks with the lowest values. We partition the sample into Expansions versus Recessions based on whether part or all of the prior year was defined as Recessionary per the NBER. We then divide the sample into halves chronologically (1981 to 2000 and 2001 to 2020) as well as by whether the value-weighted market index had an above (High_MktRet) or below median return (Low_MktRet) during the prior year.

4. Conclusion

Prior research documents a January effect in which underperforming stocks from the prior year subsequently exhibit a strong rebound in January. Given that many anomaly variables are heavily influenced by past performance, we explore the January effect's impact on several of the most well-

[2]Tests repeated with the July interaction are omitted for brevity but are available upon request.

studied anomalies. We show that the size, profitability, and momentum anomalies change signs in January, with small, unprofitable, and low prior return stocks outperforming in January but large, profitable, and high prior return stocks outperforming across the rest of the year. Additionally, there is limited evidence of a short-term reversal effect across the full year, but the effect is highly pronounced at the turn of the year. Our cross-sectional and panel regressions further highlight that several of the anomaly variables contribute significant independent explanatory power in predicting January returns. For instance, after controlling for firm size, less profitable companies with lower prior month returns still tend to outperform in January. Such evidence is relevant both from a market efficiency standpoint as well as for investors using anomaly-based investing strategies which have grown in prominence. Even in instances where market frictions make it difficult to fully exploit patterns in turn-of-the-year returns, investors may benefit by being cognizant of return seasonality, strategically adjusting portfolio weights, and avoiding poorly timed investments.

Using subsample tests to better understand the January effect, we show that return-based anomalies such as momentum and short-term reversal both display evidence of a strong reversal effect in January that is concentrated in years following recessions and poor stock market performance. Thus, in addition to the presence of return seasonality during the year, we document that the strength of the January effect and its relationship with return anomalies varies across years and is most pronounced for anomalies based on past performance when prior year investment losses are more widespread. Overall, our findings are consistent with the tax-loss harvesting explanation though additional research is needed to assess the role of other contributing factors.

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MEASURING VALUATION UNCERTAINTY: A PCA APPROACH

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Abstract

Determining which companies are more difficult to value is a topic of significant interest in finance. While prior studies have employed various univariate proxies to classify firms into high- and low-valuation uncertainty groups, this study proposes a new approach to measuring valuation uncertainty. Specifically, I employ principal component analysis (PCA) to extract the first principal component from 11 valuation uncertainty proxies. The first principal component is proposed as a comprehensive measure of a firm's valuation uncertainty. The findings demonstrate that the PCA-derived valuation uncertainty index provides two key benefits over univariate valuation uncertainty proxies. First, integrating multiple valuation uncertainty proxies into a single metric improves our ability to quantify valuation uncertainty. Second, it assists in identifying the proxies that are most informative in measuring a firm's valuation uncertainty. Ultimately, the PCA-derived valuation uncertainty index can better enable market participants to measure a firm's valuation uncertainty.

Keywords: Valuation uncertainty, hard-to-value, principal component analysis

JEL Codes: G10, G12

1. Introduction

A firm's intrinsic value is calculated by discounting its expected future cash flow at the cost of capital. However, what makes a firm difficult to value? Over the years, finance academics and practitioners have explored this question and proposed many measures as proxies for the unmeasurable latent factor of valuation uncertainty. These proxies attempt to capture the uncertainty in estimating cash flows and discount rates, both of which affect the uncertainty in estimating a firm's value. Understanding a firm's valuation uncertainty has garnered increased interest in recent years, as we have observed dramatic price dislocations between a firm's intrinsic value and its market value for many hard-to-value firms.

Valuation uncertainty is a crucial factor that influences market participants' decision-making process in several ways. For instance, the uncertainty surrounding a firm's value can lead to divergent viewpoints among investors, which, in turn, negatively impacts stock prices and makes them more volatile in response to shifts in investor sentiment (Baker & Wurgler, 2006,2007). This effect is more pronounced during market dislocations, such as during the early stages of the COVID-19 pandemic, which exposed hard-to-value stocks to significant overreactions (Xiong et al., 2020).

Valuation uncertainty also plays a vital role in risk management because firms with higher valuation uncertainty have stock values that are more sensitive to changes in market conditions or economic shocks. This increased valuation complexity increases investors' propensity to use valuation heuristics, which are subject to more potent adverse effects stemming from behavioural biases, leading to a higher likelihood of valuation mistakes (Baker & Wurgler, 2007; Kumar, 2009). Further, valuation uncertainty negatively affects market makers' bid–ask spread decisions, negatively affecting a firm's liquidity (Glosten & Milgrom, 1985). Therefore, valuation uncertainty is a fundamental concept that affects market participants' decision-making, and it is important for investors to understand the factors that contribute to valuation uncertainty and consider them in their decision-making.

Valuation uncertainty has been extensively studied in the finance literature. However, previous research has predominantly relied on many indirect and arbitrary proxies to measure a firm's valuation uncertainty. This has revealed that understanding the drivers of a firm's valuation uncertainty encompasses multiple dimensions, and a single univariate measure cannot comprehensively capture it. Moreover, relying on indirect proxies in empirical models may cause significant issues as they may introduce measures that are highly correlated with irrelevant attributes, which can create noise or bias, compromising the accuracy of the results. This lack of a direct and reliable measure of valuation uncertainty can limit our ability to gain insights from models that may be affected by impure valuation uncertainty measures. Therefore, developing a purified holistic measure of valuation uncertainty is crucial to address these issues.

Principal Component Analysis (PCA) is a statistical technique that provides an effective way of constructing a comprehensive measure of valuation uncertainty. PCA achieves this by identifying and simplifying the common information content among variables, reducing the complexity of high-dimensional correlated data, and projecting them onto a smaller set of new variables. By extracting the shared information from multiple variables, we can identify uncorrelated latent structures from the data, providing a purified and holistic measure of valuation uncertainty.

This study utilizes PCA to extract the first principal component from 11 widely used valuation uncertainty proxies, which reveals the underlying valuation uncertainty latent component. This approach results in a more precise and informative valuation uncertainty measure. This study contributes to the valuation uncertainty literature by presenting a more robust and informative measure of the valuation uncertainty latent construct. I argue that PCA offers two benefits. First, combining a wide range of valuation uncertainty proxies into one variable helps us better measure a firm's valuation uncertainty. Second, it can help determine the more meaningful proxies in measuring a firm's valuation uncertainty.

Previous research has identified several factors affecting a firm's valuation uncertainty, including Baker and Wurgler (2006, 2007), who demonstrate that younger companies with small market capitalizations, low profits, high growth, high financial distress, and low dividends are difficult to value. The rationale is that this type of firm makes estimating their future cash flows and discount rates more challenging. Other studies have presented similar proxies for valuation uncertainty as those used by Baker and Wurgler, such as small firms with high return volatility, low profitability, and high growth rates (Aboody et al., 2018; Hribar & McInnis, 2012). In addition, analysts' forecast dispersion is informative of valuation uncertainty (Güntay & Hackbarth, 2010), and dividend-paying firms tend to be easier to value (Pastor & Veronesi, 2016). Furthermore, the number of analysts covering a firm can be a proxy for its information environment, whereby higher analyst coverage reduces information asymmetry, thereby reducing valuation uncertainty (Ramnath et al., 2008).

Although prior studies have utilized univariate or bivariate measures to classify firms into valuation uncertainty groups, such approaches provide only a limited picture of the multifaceted concept of valuation uncertainty (e.g., Aboody et al., 2018; Baker & Wurgler, 2006,2007; Hribar & McInnis, 2012; Kumar, 2009). Additionally, the univariate valuation uncertainty measures employed in prior studies can be ad hoc and inadequate for fully capturing the elusive latent factor of valuation uncertainty. A comprehensive metric is necessary to capture the information content of various valuation uncertainty proxies found in the literature. The PCA approach discussed in this study provides such a metric by extracting shared information content across multiple proxies and identifying the uncorrelated latent structure, leading to a more comprehensive and dependable measure of valuation uncertainty. By moving beyond simplistic univariate or bivariate measures, we can obtain a deeper understanding of the complex nature of valuation uncertainty.

This paper is organized as follows. In section 2, I review the data and explain how PCA is applied to the valuation uncertainty proxies to extract the latent component. I present and discuss the PCA results in section 3 and offer some concluding remarks in section 4.

2. Data and methodology

2.1 Data

The initial step was to collect the proxies for a firm's valuation uncertainty. Specifically, I evaluate the firm-level valuation uncertainty proxies used in recent research and identify 11 proxies that are commonly used in the literature. The sample consists of U.S. firm-level data collected from Bloomberg and contains 1,062 publicly traded firms with observations for the fiscal period ending December 31, 2020. Table 1 presents summary statistics for the valuation uncertainty proxies used in this study[1].

Table 1: Descriptive Statistics

	Min.	Max.	Median	Mean	Std. Dev.
Analysts' EPS Dispersion	0.01	3.16	0.12	0.24	0.45
260-Day Share Price Volatility	24.72	190.54	57.89	60.99	18.94
EPS / Share Price	-0.55	0.24	0.04	0.03	0.09
EPS Volatility / Share Price	0.0005	0.2425	0.0078	0.0185	0.0334
EPS YOY Change (%)	-14.45	18.46	-0.01	0.05	3.38
Cash Flow Volatility / Share Price	0.0009	0.3087	0.0143	0.0269	0.0434
Annual Dividend Yield (%)	0	7.37	1.11	1.57	1.67
Total Analysts	1	57	10	12.52	8.59
Bloomberg 1-Year Default Prob.	0	0.164	0.002	0.0051	0.0114
Beta	0.14	2.61	1.1	1.11	0.28
Log (Market Capitalization)	3.99	14.62	8.46	8.6	1.65
Number of Firms	1,062				

Note: Table 1 reports descriptive statistics on the firm-level valuation uncertainty proxies. All data are as of December 31, 2020. A complete list and description of the variables used in the study are found in Appendix 1.

The Pearson correlations between the study variables are presented in Table 2. Several measures have moderate (0.30 to 0.49) to strong (0.50+) correlations, suggesting that they may be measuring the same latent factor (the valuation uncertainty of a firm). Consequently, isolating the common latent component measured by the 11 valuation uncertainty proxies could provide a more accurate measure of valuation uncertainty than any single proxy.

[1] To mitigate the effect of extreme outliers, analysts' EPS dispersion, EPS/share price, and EPS YOY change were winsorized at the 1% and 99% level, and the annual dividend yield, EPS volatility/share price, and cash flow volatility/share price were winsorized at the 99% level.

Table 2: Correlation Matrix

		Analysts' EPS Dispersion	1	2	3	4	5	6	7	8	9
1	**260-Day Share Price Volatility**	0.22***									
2	**EPS / Share Price**	-0.12***	-0.25***								
3	**EPS Volatility / Share Price**	0.26***	0.53***	-0.51***							
4	**EPS YOY Change (%)**	-0.15***	-0.08***	0.24***	-0.17***						
5	**Cash Flow Volatility / Share Price**	0.12***	0.40***	-0.05	0.52***	-0.05*					
6	**Annual Dividend Yield (%)**	-0.07**	-0.07**	0.10***	0.02	-0.04	0.06*				
7	**Total Analysts**	-0.05	-0.24***	-0.08***	-0.05	-0.03	-0.15***	-0.01			
8	**Bloomberg 1-Yr. Default Prob.**	0.20***	0.64***	-0.36***	0.68***	-0.17***	0.46***	0.04	-0.07**		
9	**Beta**	0.03	0.69***	-0.16***	0.27***	-0.03	0.26***	0.01	-0.07**	0.40***	
10	**Log (Market Capitalization)**	-0.21***	-0.49***	0.04	-0.26***	0.02	-0.26***	0.02	0.80***	-0.29***	-0.19***

Note: Table 2 presents the correlation matrix for the variables used in the study. The numbers are the Pearson correlations. A complete list and description of the variables used in the study are found in Appendix 1. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively.

2.2 Methodology

Using the 11 valuation uncertainty proxies, principal component analysis was applied to extract the latent structures in the valuation uncertainty proxies. PCA is a technique used to find patterns in data to decrease redundancy in univariate analysis when collinear data are employed (Adbi & Williams, 2010). PCA restructures the datasets with correlated variables into uncorrelated components of the original variables. In addition, new values are computed for each orthogonal component, which can be utilized to replace the original correlated variables and be used as a more holistic valuation uncertainty index.

Eigen decomposition is the standard method for conducting PCA. Decomposition is conducted on an $n \times n$ matrix representing the relationship between all pairs of n variables (in this case, the valuation uncertainty measures). Then, depending on the nature of the variable, either the covariance or correlation matrix is input into the eigen decomposition (Adbi & Williams, 2010). Because the valuation uncertainty measures used in the study are on various scales, a correlation matrix is utilized. Furthermore, the valuation uncertainty measures are normalized by scaling each measure before performing the eigen decomposition. Each derived eigenvector is treated as a principal component; that is, the numeric values in each eigenvector are the coefficients of each principal component, which can be thought of as the valuation uncertainty proxy weights.

A varimax PCA rotation is employed to better interpret the component loadings[2] (i.e., how closely the valuation uncertainty proxies relate to the principal component). Varimax rotation is an orthogonal rotation that maximizes the squared variance of the component loadings (Adbi & Williams, 2010). Therefore, it prioritizes either very high or extremely low loadings, making it simpler to understand the latent structure represented by each component.

[2] The PCA analysis was re-run using an oblique rotation and the results were unchanged.

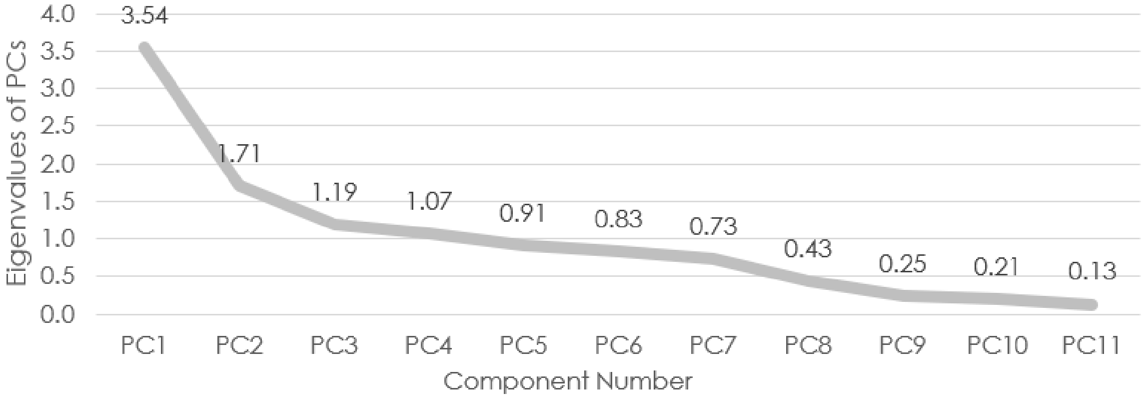
In addition, regression is used to integrate the measurements and derive the latent components[3]. The component scores explain the linear combination of measurements to generate each component. This regression method estimates the projection of each data point along each PCA component as a function of the original n measures for each PCA component. Finally, the calculated regression coefficients for a specific component are referred to as the component loadings and offer a way to linearly combine the *n* measurements to generate the latent component. By analyzing component loadings, we can determine which valuation uncertainty proxies have a more potent effect on the valuation uncertainty latent component.

Finally, for PCA to be reliable, three key assumptions must be met:1) sphericity or the existence of an identity matrix, 2) sampling adequacy or a sufficient number of observations related to the number of variables being evaluated, and 3) confirmation that there is a positive determinant of the correlation matrix. First, using the Bartlett test, I confirmed that the matrix is derived from a collinear population ($X^2 = 415.45$, $p<.01$). Second, Jung (2013) argues that 50 observations per measure are sufficient, and the minimum number required declines as the number of retained factors decrease. Given that there are over 98 observations per measure in this study (1,062 firms divided by 11 valuation uncertainty proxies) and that only one latent component is retained as a measure of a firm’s valuation uncertainty, the number of observations is deemed to be sufficient to continue. Finally, a positive determinant of the correlation matrix is computed. Thus, all PCA assumptions were met. The PCA analysis is reported in the next section.

3. Empirical Results

Principal component analysis was performed[4]; Figure 1 presents the scree plot of the eigenvalues for the 11 latent components extracted using PCA. Principal component 1 (PC1) explains 32.2% (3.54/11) of the total variance in the valuation uncertainty proxies, whereas principal component 2 explains only 15.5% (1.71/11), suggesting that only the first principal component should be retained. Further, using Velicer’s (1976) minimum absolute partial correlation (MAP) criterion, it is determined that one factor achieves the MAP of 0.05. Thus, only one principal component is retained, serving as the latent measure of a firm’s valuation uncertainty.

Figure 1: Scree Plot



Note: The figure presents the eigenvalues of the principal components extracted using PCA.

[3] See DiStephano et al. (2008) for an overview of the different alternatives.
[4] The R package “psych” version 2.1.9 was used for the PCA analysis.

Table 3, column 1 presents the component loadings (i.e., correlation values in the range [-1,+1]) between the valuation uncertainty proxies and the first latent component. The measures have been sorted from the highest positive loadings on top to the lowest negative loadings at the bottom. Further, the root mean square of the off-diagonal residuals is 0.14 with a X^2= 2,287.47 and p<.01, confirming that 1 component is sufficient.

Consistent with the literature, the valuation uncertainty proxies that positively relate to the valuation uncertainty latent measure (PC1) are as follows, from greatest to least effect: 260-day share price volatility, one-year default probability, EPS volatility, cash flow volatility, beta, and analysts' EPS dispersion. On the other hand, the valuation uncertainty proxies negatively related to the valuation uncertainty latent measure (PC1) include, from greatest to least effect, market capitalization, profitability (EPS/share price), the number of analysts covering the company, the EPS year-over-year change, and the annual dividend yield. Consequently, PC1 effectively isolates the common component among the 11 valuation uncertainty proxies, thus more holistically measuring the valuation uncertainty latent structure and thereby supporting its use as a comprehensive index of a firm's valuation uncertainty.

In addition, the component loadings for each valuation uncertainty proxy on the valuation uncertainty index (PC1) can be used to identify the most influential contributors to a company's valuation uncertainty. Table 3, column 2 displays the relative significance of each measure of valuation uncertainty (defined as the relative magnitude of the PC1 loading's absolute value). According to the PCA results, the three most influential proxies for a company's valuation uncertainty are the 260-Day share price volatility, the Bloomberg one-year default probability, and the EPS volatility; conversely, the three least influential proxies are the annual dividend yield, the EPS year-over-year change, and the analysts' EPS dispersion.

Table 3: PCA Results

Valuation Uncertainty Proxy	(1) Principal Component 1	(2) Relative Importance
260-Day Share Price Volatility	0.853	1
Bloomberg 1-Year Default Prob.	0.806	2
EPS Volatility / Share Price	0.785	3
Cash Flow Volatility / Share Price	0.612	4
Beta	0.592	5
Analysts' EPS Dispersion	0.338	9
Annual Dividend Yield (%)	-0.015	11
EPS YOY Change (%)	-0.219	10
Total Analysts	-0.347	8
EPS / Share Price	-0.437	7
Log (Market Capitalization)	-0.590	6

Note: Column 1 presents the loadings for each valuation uncertainty proxy to principal component 1 (PC1). PC1 is then computed for each firm as the sum weight of the PC1 component loading x the observed valuation uncertainty proxy measure. Column 2 presents the relative importance of each valuation uncertainty proxy in measuring the PC1 latent component. A complete list and description of the variables used in the study are found in Appendix 1.

Next, using the valuation uncertainty index (PC1), firms are sorted into terciles. Firms with a valuation uncertainty index of -0.407 or less are classified as "low valuation uncertainty," firms with a valuation uncertainty index above -0.407 and up to 0.128 are classified as "average valuation uncertainty," and firms with a valuation uncertainty index greater than 0.128 are classified as having "high valuation uncertainty."

Table 4 presents the mean, median, and standard deviation of the 11 valuation uncertainty proxies by the valuation uncertainty index (PC1) tercile group. The results are consistent with prior literature, revealing that firms in the low valuation uncertainty group have the lowest analysts' EPS dispersion, 260-day share price volatility, EPS volatility, cash flow volatility, one-year default probability, and beta. Additionally, these firms have the highest levels of profitability (EPS/share price), EPS year-over-year change, number of analysts covering the firm, and market capitalization, suggesting that they are relatively easier to value. Conversely, firms in the high valuation uncertainty group exhibit a reversed relationship, indicating that they are more difficult to value.

The final column of Table 4 reports the results of the independent t-test evaluating the difference in the means for the high versus low valuation uncertainty groups for each respective valuation uncertainty proxy. The p-values for all t-tests, except for annual dividend yield, are below 0.01, indicating that the difference between the high and low valuation groups is statistically significant. However, there is no consistent relationship between the annual dividend yield and the valuation uncertainty groups, and the corresponding t-test indicates that the difference is not statistically significant. Table 3 shows that the annual dividend yield has the lowest loading to the valuation uncertainty index of all the proxies (0.015), indicating that the measure is the least useful proxy for identifying hard-to-value firms.

Table 4: Descriptive Statistics by PCA Terciles

	PC1 Tercile #1 Low Uncertainty (n=354)			*PC1 Tercile #2 Avg. Uncertainty (n=354)*			*PC1 Tercile #3 High Uncertainty (n=354)*			*High-Low Groups*	
	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Mean Difference	*t*-statistic
Analysts' EPS Dispersion	0.08	0.11	0.12	0.12	0.18	0.21	0.19	0.44	0.7	0.32	8.64***
260-Day Share Price Volatility	45.3	45.38	7.57	58.07	58.54	7.61	75.58	79.04	19.64	33.66	30.10***
EPS / Share Price	0.03	0.04	0.03	0.05	0.04	0.04	0.03	0	0.15	-0.04	-4.26***
EPS Volatility / Share Price	0.0042	0.0063	0.0058	0.0071	0.0105	0.0108	0.0195	0.0387	0.0508	0.03	11.92***
EPS YOY Change (%)	0.06	0.43	2.76	0.03	0.41	3.01	-0.26	-0.67	4.1	-1.09	-4.15***
Cash Flow Volatility / Share Price	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.05	0.06	0.04	12.31***
Annual Dividend Yield (%)	1.07	1.4	1.39	1.38	1.74	1.72	0.8	1.56	1.86	0.15	1.24
Total Analysts	18	18.73	8.98	8	9.91	6.24	7	8.91	6.59	-9.83	-16.60***
Bloomberg 1-Year Default Prob.	0.0005	0.0009	0.0013	0.002	0.0026	0.0026	0.007	0.0119	0.0177	0.01	11.67***
Beta	0.89	0.91	0.2	1.12	1.12	0.19	1.3	1.3	0.29	0.39	20.92***
Log (Market Capitalization)	9.99	10.08	1.31	8.29	8.29	1.11	7.44	7.43	1.24	-2.65	-27.70***
Valuation Uncertainty Index (PC1)	-0.78	-0.82	0.28	-0.14	-0.14	0.15	0.56	0.96	1.13	1.78	28.69***

Note: Table 4 displays the median, mean, and standard deviation for the valuation uncertainty proxy measure (PC1) used in the study and the valuation uncertainty proxies used in the study by PC1 terciles, where the first tercile is designated the low valuation uncertainty group, the second tercile is the average valuation uncertainty group, and the third tercile is the high valuation uncertainty group. The last column presents the independent t-test statistic comparing the means for the high-uncertainty group to the low-uncertainty group. *** denotes significance at the 0.01 level.

As a robustness check, I compare the valuation uncertainty groups (derived using the PCA method described in this section) to the clusters formed using the partition around medoids (PAM) clustering algorithm, where the Manhattan distance is used to measure similarity. PAM provides a more robust version of the k-means algorithm: while *k*-means clustering aims to minimize intra-cluster distance, *k*-medoid minimizes the dissimilarities between points in a cluster and points considered to be the centres of that cluster, thereby producing a more robust result (Kaufman & Rosseeuw, 1990). Using the PAM algorithm and 11 valuation uncertainty proxies, firms are clustered into three groups, with the first cluster containing 383 firms, the second containing 371 firms, and the third containing 308 firms.

Table 5 provides a detailed analysis of the 11 valuation uncertainty measures for the PAM-derived cluster groups. The table presents the mean, median, and standard deviation for each measure, while the last column displays the results of the independent *t*-test. The *t*-test compares the difference in the means for the high versus low-valuation uncertainty groups for each valuation uncertainty proxy. The summary statistics in Table 5 reveal that the firms in Cluster 1 exhibit low valuation uncertainty, cluster 2 contains firms with average valuation uncertainty, and Cluster 3 contains firms with high valuation uncertainty. Notably, seven valuation uncertainty proxies exhibit a relationship consistent with their uncertainty classification (low, average, and high), including the five proxies with the highest loadings to PC1.

It is worth noting that the remaining valuation uncertainty proxies do not always exhibit a relationship consistent with their valuation uncertainty designation. This inconsistency can be attributed to the fact that these proxies represent the least informative measures for constructing the valuation uncertainty index (PC1), and are, therefore, less informative in driving the construction of the clusters. Consequently, the application of the PAM algorithm to these measures can produce mixed results. Nevertheless, the *t*-test evaluating the difference in the means for the high versus low valuation uncertainty groups indicates that the difference in means for all the valuation uncertainty proxies, except for the EPS year-over-year change measure, is statistically significant at the .01 level.

Table 5: Descriptive Statistics by PAM Clusters

	Cluster #1 Low Uncertainty (n=383)			*Cluster #2 Avg. Uncertainty (n=371)*			*Cluster #3 High Uncertainty (n=308)*			*High-Low Groups*	
	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	*Mean Difference*	*t*-statistic
Analysts' EPS Dispersion	0.09	0.15	0.21	0.11	0.24	0.48	0.18	0.35	0.57	0.2	6.00***
260-Day Share Price Volatility	45.97	46.89	8.68	57.34	58.09	9.06	76.72	80.76	19.56	33.87	28.24***
EPS / Share Price	0.03	0.03	0.03	0.05	0.05	0.07	0.03	0	0.15	-0.03	-3.59***
EPS Volatility / Share Price	0.0045	0.0088	0.0123	0.0077	0.0147	0.0227	0.0144	0.0343	0.0507	0.03	8.62***
EPS YOY Change (%)	0	0.14	2.7	0	-0.05	2.54	-0.09	0.08	4.7	-0.05	-0.17
Cash Flow Volatility / Share Price	0.01	0.01	0.02	0.02	0.03	0.03	0.02	0.04	0.06	0.03	8.10***
Annual Dividend Yield (%)	1	1.31	1.41	2.51	2.44	1.72	0	0.83	1.41	-0.48	-4.46***
Total Analysts	19	20.06	7.97	6	7.14	4.26	8	10.11	6.74	-9.95	-17.77***
Bloomberg 1-Year Default Prob.	0.0005	0.0013	0.0022	0.0022	0.0037	0.0077	0.0064	0.0113	0.0174	0.01	10.05***
Beta	0.92	0.95	0.22	1.07	1.06	0.18	1.35	1.35	0.28	0.4	20.55***
Log (Market Capitalization)	10.08	10.21	1.2	7.76	7.73	1.07	7.84	7.76	1.21	-2.44	-26.39***

Note: Table 5 displays the median, mean, and standard deviation for the valuation uncertainty proxies used in the study by the PAM clusters compiled from the 11 valuation uncertainty proxies. The last column presents the independent t-test statistic comparing the means for the high-uncertainty group to the low-uncertainty group. *** denotes significance at the 0.01 level.

To further assess the efficacy of the PCA-based valuation uncertainty index and the PAM clustering algorithm, I performed a comparison of the valuation group designation resulting from the two methods. I find that 73.26% of the firms are classified consistently as low, average, or high valuation uncertainty between the two methods. Additionally, the correlation between their respective classification groupings (1, 2, 3) is 0.78, indicating a high level of agreement between the two methods. These results suggest that the valuation uncertainty index constructed using PCA is a robust measure of a firm's valuation uncertainty, as it generates similar valuation group designations as the PAM clustering algorithm.

4. Conclusion

Understanding a firm's valuation uncertainty is essential for investors, analysts, and other market participants in making informed decisions. However, prior studies have relied on several univariate proxies to measure a firm's valuation uncertainty, providing only a partial picture of this complex, multifaceted, and elusive latent factor. To overcome this limitation, this study employs PCA to create a purified and comprehensive measure of valuation uncertainty that captures the information content of 11 proxies.

The findings demonstrate that the valuation uncertainty index derived from these 11 proxies accurately captures a firm's valuation uncertainty and aligns with the results of the PAM clustering algorithm. PCA provides two significant advantages. Firstly, it permits the merging of various proxies for valuation uncertainty into one inclusive metric, thus enhancing the ability to measure it more comprehensively. Secondly, it enables the identification of the most informative proxies for determining the factors that drive a firm's valuation uncertainty.

The findings have significant implications for market participants seeking to understand the impact of valuation uncertainty on financial markets. By offering a comprehensive measure of a firm's valuation uncertainty, this study contributes to an improved understanding of how to measure valuation uncertainty efficiently and holistically. Ultimately, the PCA-derived valuation uncertainty index can assist investors, analysts, and other market participants in better measuring a firm's valuation uncertainty.

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Appendix 1: Definition of Variables

Variable	Definition
EPS Dispersion	Measures the dispersion of the analyst EPS estimates around their mean value as of December 31, 2020. The standard deviation of analysts' quarterly EPS estimates as of December 31, 2020, is divided by the average EPS estimate (before extraordinary items).
260-Day Share Price Volatility	A measure of the risk of price moves for a stock calculated from the standard deviation of day-to-day logarithmic historical price changes. The 260-day price volatility equals the annualized standard deviation of the relative price change for the 260 most recent trading days' closing price, expressed as a percentage.
EPS / Share Price	The trailing 12 months' earnings per share are normalized by the share closing price.
EPS Volatility / Share Price	The quarterly EPS volatility for 2015 – 2020 normalized by the 12/31/2020 share closing price
EPS YOY Change (%)	The year-over-year change in the firm's quarterly EPS as of 12/31/2020.
Cash Flow Volatility / Share Price	The quarterly cash flow per share volatility for 2015 – 2020 normalized by the 12/31/2020 share closing price.
Annual Dividend Yield (%)	The sum of dividend per share amounts that have gone ex-dividend over the prior 12 months, divided by the current stock price, expressed as a percentage.
Total Analysts	The total number of analysts making recommendations for the firm as of 12/31/2020.
Bloomberg 1-Year Default Prob.	The probability of default of the firm over the next 1-year is calculated by the Bloomberg Issuer Default Risk model.
Log (Market Capitalization)	The log of the total current market value of a company's outstanding shares is stated.
Beta	Measures the volatility of the stock price relative to the volatility in the market index. Beta is the percent change in the price of the stock given a 1% change in the market index.

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EQUITY PLEDGE, PLEDGOR TYPE AND INVESTMENT EFFICIENCY

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Abstract

Equity pledging is susceptible to agency problems and substantial risk, resulting in inefficient corporate investment. We show that the negative impact is not just induced by controlling shareholders but also pledged by non-controlling shareholders. Our results add that SOEs with control rights via controlling shareholders or actual controllers can mitigate investment inefficiency problems. We conclude that pledgor-type matters and the impact of non-controlling shareholders' pledges should not be neglected.

Keywords: agency problem, equity pledge, controlling shareholders, non-controlling shareholders, actual controller, investment efficiency

JEL Codes: G3

1. Introduction

Equity pledging is a standard financing method for controlling shareholders in China to raise capital while retaining their control rights. The market for equity pledging in China is enormous. In 2021, pledged shares had a market value of 4.18 trillion yuan (refer to Table 1). Studies find that controlling shareholders' pledges exacerbate agency conflicts due to margin call stress (Chan et al., 2018; Chauhan et al., 2021). If pledgors fail to satisfy the margin call when the pledged share price falls below the threshold, pledgees can forcibly sell the shares, and pledgors risk losing control. Therefore, controlling shareholders are inclined to change their incentives and influence corporate decisions in various ways to avoid margin calls. One way is to alter capital investment risk that can impair corporate investment efficiency.

Pledged firms are incentivized to lower capital investment risk (Chauhan et al., 2018) by reducing capital expenditures, including R&D expenses, compared to non-pledged firms to keep the personal benefits of pledging (Dou et al., 2019). Insiders tend to forgo risky but profitable investment opportunities (Dou et al., 2019) to moderate investment risk directly reflected in the firm's stock return volatility and future stock price crash risk, causing underinvestment problems. In contrast, pledged firms may have a larger risk appetite because the pledgors know that the downside risk is limited. In the worst-case scenario, the pledged shares would be liquidated to meet margin calls. The unlimited upside potential could motivate controlling shareholders to overinvest by undertaking risky but profitable investments to boost share prices at the expense of minority shareholders (Dou et al., 2019;

Ren et al., 2022) or debtholders (Chauhan et al., 2021). In both cases, equity pledges intensify firms' agency problems.

Table 1: Market value of pledged shares from 2014 to 2021

Year	Number of firms with pledged shares	Market value of pledged shares (in trillion yuan)
2014	2,545	2.58
2015	2,774	4.93
2016	2997	5.44
2017	3,433	6.15
2018	3,434	4.23
2019	3,081	4.72
2020	2,632	4.32
2021	2,517	4.18

Note: This table shows the number of firms with pledged shares and the market value of pledged shares in China in trillion yuan. The statistics are sourced from http://www.chinaclear.cn/

However, these studies are limited to controlling shareholders' pledges. We fill the gap by examining the effect of equity pledging by pledgor type on investment efficiency. We identify the pledgors into three main types: controlling shareholders; non-controlling shareholders; and actual controllers. Though non-controlling shareholders are often perceived to exert less impact on corporate decision-making, we argue that non-controlling shareholders' pledges can have an indirect but significant impact on corporate investment efficiency. This is because non-controlling shareholders' pledges are subject to the same margin call pressure that can drive up firms' crash risk. If the pledged share prices fall below the threshold, the pledgees can forcibly sell the shares if the non-controlling shareholders fail to meet the margin calls. The forced selling will add downward pressure to the share prices, and the adverse effects will spill over to other shareholders.

In the event of forced selling, controlling shareholders' wealth will be critically affected, given their substantial interest in the firms. Controlling shareholders are, therefore, incentivized to influence corporate investment decisions to protect their interests, mitigating the firms' adverse spillover effects from non-controlling shareholders' pledges. Depending on the incentives, non-controlling shareholder pledges can also lead to underinvestment or overinvestment problems. Underinvestment tends to happen when the incentive is to sustain the share price, where firms take less to moderate investment risk, forgoing risky but profitable investment opportunities. In contrast, overinvestment is driven by substantial risk-taking to boost the share price. Based on the argument, we expect non-controlling equity pledges to negatively affect firms' investment efficiency.

An actual controller typically refers to a non-shareholder with control rights to influence corporate decisions through investment relationships or other arrangements. In the case of equity pledging, the actual controller is the firm's shareholder that holds and pledges shares of another firm. Actual controllers are expected to use their control rights to influence corporate investment policies. If their goal is to maximize shareholders' wealth, then they are expected to act in the best interest of all shareholders. Suppose their incentives outweigh the shareholders' value-maximizing goal; they will likely influence corporate decisions based on their incentives, such as trading the equity pledging risk with corporate investment.

Our study contributes additional insights to the growing literature on equity pledges. In fact, existing evidence does imply that firm and pledgor type matter, but the evidence is still limited. Previous studies mainly compare the impact of controlling shareholders' pledges between non-state-owned enterprises (non-SOEs) and SOEs (Deren & Ke, 2018; Huang et al., 2022). In addition, Li et al. (2019) examine the impact of the largest shareholders' pledges on crash risk, whereas in our study we extend by considering pledgor type. We show that the negative effect of equity pledges on investment efficiency is not solely instigated by controlling shareholders, but also by non-controlling shareholders. Actual controllers' pledges do not significantly impact investment efficiency. Probably, this is because actual controllers do not have direct ownership, and their pledges are insubstantial. We add that SOE-related pledgors can mitigate the investment efficiency of pledged firms. In addition, this study contributes to the literature on agency theory. Our findings suggest that pledged shareholders can exacerbate agency conflicts (Chan et al., 2018) by directly or indirectly (in the case of non-controlling shareholders' pledges) influencing corporate investment decisions to reduce the riskiness of firms caused by equity pledging. This results in inefficient investment at the expense of non-pledged shareholders and other stakeholders.

The remaining sections of the paper are structured as follows: Section 2 details the data and methodology. The results are discussed in Section 3, and the study is concluded in Section 4.

2. Data and methodology

Our sample consists of 3,434 Chinese A-share listed firms on the Shanghai and Shenzhen stock exchanges from 2010 to 2020. We exclude financial firms, special treatment firms (ST and *ST firms), or suspended firms with delisting risks to control for the differences in the risk characteristics. We have an unbalanced panel dataset of 19,072 firm-year observations. The dataset is collected from the Wind database. The continuous variables are winsorized at 1% in each tail to control for potential outliers.

Investment efficiency, *InvEff*, is measured using residuals, $\varepsilon_{i,t}$, derived from Richardson's (2006) investment expectation model as follows.

$$Inv_{i,t} = \beta_0 + \beta_1 Q_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Lev_{i,t-1} + \beta_4 Cash_{i,t-1} + \beta_5 Age_{i,t-1} + \beta_6 Return_{i,t-1} + \beta_{17} Inv_{i,t-1} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{1}$$

$\varepsilon_{i,t}$ is the difference between actual and expected investment level. A higher $\varepsilon_{i,t}$ indicates a higher level of investment inefficiency. We multiple $|\varepsilon_{i,t}|$ with -1, so that a higher $-|\varepsilon_{i,t}|$ denotes a higher investment efficiency because there is a lower deviation from the expected investment (Cao et al., 2020; Gomariz & Ballesta, 2014). We test our hypothesis using the multivariate panel data regression model, controlling for year and industry-fixed effects, with standard errors clustered at the firm level.

$$InvEff_{i,t} = \beta_0 + \beta_1 Pledge_{i,t} + \beta_2 Growth_{i,t} + \beta_3 Size_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Cash_{i,t} + \beta_6 Age_{i,t} + \beta_7 ROA_{i,t} + \beta_8 Tangibility_{i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{2}$$

Equity pledge is measured by a dummy variable, *D_Pledge* and pledge ratio, *Pledge*. We expect β_1 to be negative, implying that share pledging leads to firms' investment inefficiency.

We categorize the pledge ratio by controlling, non-controlling, and actual controllers. We also control for growth, firm size and age, leverage levels, cash flows, and profitability, which commonly affect investment efficiency. Table A lists the descriptions of the variables.

3. Results and Discussion

From Table 2, the mean (median) values of *Inveff, Overinv*, and *Underinv* are -0.0372 (-0.0239), 0.0491 (0.0259), and -0.0301 (-0.0233), respectively. Consistent with Huang et al. (2022), Chinese firms are inclined to underinvestment problems. 46.75% of the observations are pledged firms, where 30.10% are share pledges by controlling shareholders, followed by non-controlling shareholders' pledges of 16.30%, and actual controllers' pledges of 2.19%.

Table 2: Summary statistics

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
InvEff	19072	-0.0372	-0.0239	0.0439	-0.2761	0.0000
OverInv	7172	0.0491	0.0259	0.0615	0.0000	0.2761
UnderInv	11897	-0.0301	-0.0233	0.0260	-0.1217	0.0000
D_Pledge	19072	0.4675	0.0000	0.4990	0.0000	1.0000
D_Controlling	19072	0.3010	0.0000	0.4587	0.0000	1.0000
D_Non-controlling	19072	0.1630	0.0000	0.3694	0.0000	1.0000
D_Actual	19072	0.0219	0.0000	0.1462	0.0000	1.0000
Pledge	19072	0.0741	0.0000	0.1179	0.0000	0.5364
Controlling	19072	0.0448	0.0000	0.0920	0.0000	0.4371
Non-controlling	19072	0.0156	0.0000	0.0478	0.0000	0.2862
Actual	19072	0.0010	0.0000	0.0074	0.0000	0.0651
Q	19072	2.0794	1.6197	1.4013	0.8496	8.8981
Size	19072	22.4173	22.2432	1.2872	19.8653	26.2734
Lev	19072	0.4467	0.4415	0.2035	0.0595	0.9077
Cash	19072	0.1648	0.1364	0.1121	0.0148	0.5812
Age	19072	2.4090	2.4849	0.5842	1.0986	3.2958
Profitability	19072	0.0338	0.0328	0.0636	-0.2391	0.2056
Tangibility	19072	0.4494	0.4384	0.2032	0.0474	0.909

Note: This table summarizes the descriptive statistics of the identified variables. The total sample has 19,072 firm-year observations, where 7,172 firm-year observations are for the overinvestment subsample, and 11,897 firm-year observations are for the underinvestment subsample. The description for each variable is defined in Table A in the appendix.

In columns 1 and 2 of Table 3, *D_Pledge* and *Pledge* are negatively significant at the 1% level, indicating that equity pledging hurts investment efficiency. To avoid margin calls, pledged firms either end up overinvesting or underinvesting. If the pledge firms aim to boost share prices, they will likely take on more investment risk by overinvesting in risky projects. Alternatively, firms may forgo risky investments if firms aim to moderate investment risk to sustain share prices. Our results are also economically significant. Referring to column 2, when the equity pledge increases by 1%, investment efficiency decreases by 1.03% (0.0384/0.0372). The negative impact is greater among the overinvestment firms, where a 1% increase in equity pledging worsens overinvestment by 1.96% (0.0729/0.0372) (column 4) compared to 0.37% (0.0136/0.0372) of underinvestment (column 6).

Table 3: Equity pledge and investment efficiency

	InvEff (1)	InvEff (2)	OverInv (3)	OverInv (4)	UnderInv (5)	UnderInv (6)
D_Pledge	-0.0071***		0.0114***		-0.0028***	
	(0.0000)		(0.0000)		(0.0000)	
Pledge		-0.0384***		0.0729***		-0.0136***
		(0.0000)		(0.0000)		(0.0000)
Q	-0.0017***	-0.0017***	0.0014	0.0015*	-0.0021***	-0.0021***
	(0.0000)	(0.0000)	(0.1116)	(0.0812)	(0.0000)	(0.0000)
Size	0.0022***	0.0020***	-0.0035***	-0.0031***	0.0021***	0.0020***
	(0.0000)	(0.0000)	(0.0001)	(0.0005)	(0.0000)	(0.0000)
Lev	-0.0178***	-0.0168***	0.0409***	0.0386***	0.0001	0.0004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9673)	(0.8291)
Cash	-0.0282***	-0.0274***	0.0316***	0.0301***	-0.0263***	-0.0259***
	(0.0000)	(0.0000)	(0.0003)	(0.0004)	(0.0000)	(0.0000)
Age	0.0084***	0.0083***	-0.0116***	-0.0114***	0.0057***	0.0058***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Profitability	-0.0608***	-0.0615***	0.1247***	0.1260***	0.0053	0.0053
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2677)	(0.2715)
Tangibility	-0.0553***	-0.0553***	0.0930***	0.0928***	-0.0204***	-0.0205***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0610***	-0.0580***	0.0742***	0.0649***	-0.0739***	-0.0733***
	(0.0000)	(0.0000)	(0.0001)	(0.0004)	(0.0000)	(0.0000)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj R^2	0.1085	0.1124	0.1381	0.1480	0.1437	0.1446
Obs	19,072	19,072	7,172	7,172	11,897	11,897

Note: This table reports the regression results of the impact of equity pledging on corporate investment efficiency for the total sample (*InvEff*), overinvestment (*OverInv*), and underinvestment (*UnderInv*) subsamples. The descriptions of the variables are summarized in Table A in the appendix. The superscripts *, **, and *** indicate significance at the 90%, 95%, and 99% confidence levels, respectively.

Regarding the control variables, large-sized and older firms have higher investment efficiency because these firms are more diversified, established, and have more investment experience. Therefore, they are less likely to have over-and underinvestment problems than small-sized and younger firms (Benlemlih & Bitar, 2018; Chen et al., 2011). However, firms with high growth opportunities, leverage ratio, cash ratio, profitability, and tangibility are associated with lower investment efficiency. High-growth firms are commonly associated with underinvestment, particularly among firms with high agency problems between shareholders and debtholders (Myers, 1977). The leverage ratio accounts for firms' financial risk and constraints (Chen et al., 2011). Firms with higher leverage ratios are less likely to obtain additional financing to finance their investment opportunities, which constrains firms' investment potential. The availability of internal funding can also trigger investment inefficiency. Our results show that firms with higher profitability are induced to overinvest because profitable firms tend to have higher retained earnings.

In Table 4, we categorize the share pledges by the pledgor type. Pledgor type is measured using respective pledge ratio and dummy variable. Columns 1 to 4 show that controlling and non-controlling equity pledges lead to investment inefficiency, which is statistically significant at the 1% level. Column 5 shows that *Actual* is insignificant, but *D_Actual* is marginally significant at the 10% level (column 6). Columns 7 and 8 include the three types of pledgors in the same regression model. The coefficients of *D_Controlling* and *D_Non-controlling* (in column 7) and *Controlling* and *Non-controlling* (in column 8) remain significantly negative at the 1% level, supporting our hypotheses.

Table 4: Pledgor type and investment efficiency

	Investment efficiency (*InvEff*)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_Controlling	-0.0043*** (0.0000)						-0.0066*** (0.0000)	
Controlling		-0.0253*** (0.0000)						-0.0321*** (0.0000)
D_Non-controlling			-0.0049*** (0.0000)				-0.0076*** (0.0000)	
Non-Controlling				-0.0498*** (0.0000)				-0.0611*** (0.0000)
D_Actual					-0.0042 (0.1264)		-0.0008 (0.7936)	
Actual Controller						-0.1085* (0.0717)		-0.0228 (0.7158)
Q	-0.0016*** (0.0000)	-0.0016*** (0.0000)	-0.0016*** (0.0000)	-0.0017*** (0.0000)	-0.0016*** (0.0000)	-0.0017*** (0.0000)	-0.0017*** (0.0000)	-0.0017*** (0.0000)
Size	0.0023*** (0.0000)	0.0022*** (0.0000)	0.0023*** (0.0000)	0.0022*** (0.0000)	0.0023*** (0.0000)	0.0023*** (0.0000)	0.0022*** (0.0000)	0.0020*** (0.0000)
Lev	-0.0181*** (0.0000)	-0.0178*** (0.0000)	-0.0192*** (0.0000)	-0.0191*** (0.0000)	-0.0191*** (0.0000)	-0.0191*** (0.0000)	-0.0179*** (0.0000)	-0.0174*** (0.0000)
Cash	-0.0268*** (0.0000)	-0.0266*** (0.0000)	-0.0274*** (0.0000)	-0.0273*** (0.0000)	-0.0267*** (0.0000)	-0.0267*** (0.0000)	-0.0283*** (0.0000)	-0.0277*** (0.0000)
Age	0.0093*** (0.0000)	0.0093*** (0.0000)	0.0096*** (0.0000)	0.0096*** (0.0000)	0.0098*** (0.0000)	0.0098*** (0.0000)	0.0084*** (0.0000)	0.0087*** (0.0000)
Profitability	-0.0604*** (0.0000)	-0.0605*** (0.0000)	-0.0614*** (0.0000)	-0.0614*** (0.0000)	-0.0608*** (0.0000)	-0.0608*** (0.0000)	-0.0610*** (0.0000)	-0.0610*** (0.0000)
Tangibility	-0.0560*** (0.0000)	-0.0560*** (0.0000)	-0.0563*** (0.0000)	-0.0563*** (0.0000)	-0.0565*** (0.0000)	-0.0565*** (0.0000)	-0.0553*** (0.0000)	-0.0556*** (0.0000)
Constant	-0.0659*** (0.0000)	-0.0649*** (0.0000)	-0.0678*** (0.0000)	-0.0661*** (0.0000)	-0.0692*** (0.0000)	-0.0689*** (0.0000)	-0.0613*** (0.0000)	-0.0594*** (0.0000)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.1049	0.1056	0.1046	0.1059	0.1032	0.1033	0.1083	0.1098
Obs	19,072	19,072	19,072	19,072	19,072	19,072	19,072	19,072

Note: This table reports the regression results of the impact of equity pledging on corporate investment efficiency by the pledgor type. The descriptions of the variables are summarized in Table A in the appendix. The superscripts *, **, and *** indicate significance at the 90%, 95%, and 99% confidence levels, respectively.

Overall, our results suggest that the negative impact of equity pledges on investment efficiency is not solely driven by controlling shareholders' pledges but also by non-controlling shareholders. In contrast, actual controller pledges have no consistent or significant impact on investment inefficiency. This is likely because actual controllers do not have direct ownership, and their pledges are not substantial (refer to Table 2). Regarding economic magnitude, the adverse effect of equity pledging on investment efficiency is more substantial for non-controlling than controlling shareholders, with an economic magnitude of 1.34% (0.0498/0.0372, column 2) compared to 0.68% (0.0253/0.0372, column 1) if pledges by respective group increases by 1%.

Next, we re-estimate Equation 2 with firm fixed effect to alleviate possible endogeneity concerns because of differences across firms. The results are reported in Table 5. We also control for bias that may be caused by reverse causality and lagged effect. We lag the pledge and control variables by one year (Huang et al., 2022; Wu et al., 2022) so that the study can account for year-end equity pledges' impacts on investment efficiency. The results are reported in Table 6. In both robustness analyses, our results remain consistently significant as those reported in Table 4. Equity pledging is negatively related to investment efficiency, mainly driven by controlling and non-controlling shareholders' pledges. Actual control pledges are reported to have an insignificant effect on corporate investment efficiency.

Table 5: Controlling for firm fixed effect

	Investment efficiency (*InvEff*)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_Controlling	-0.0053*** (0.0089)						-0.0078*** (0.0091)	
Controlling		-0.0287*** (0.0081)						-0.0358*** (0.0070)
D_Non-controlling			-0.0058*** (0.0051)				-0.0089*** (0.0045)	
Non-Controlling				-0.0555*** (0.0038)				-0.0671*** (0.0038)
D_Actual					-0.0052 (0.1479)		-0.0010 (0.7367)	
Actual Controller						-0.1277 (0.1014)		-0.0309 (0.5974)
Q	-0.0019*** (0.0004)	-0.0019*** (0.0004)	-0.0019*** (0.0006)	-0.0020*** (0.0005)	-0.0019*** (0.0005)	-0.0020*** (0.0005)	-0.0019*** (0.0006)	-0.0020*** (0.0004)
Size	0.0025*** (0.0001)	0.0025*** (0.0001)	0.0026*** (0.0000)	0.0026*** (0.0001)	0.0027*** (0.0000)	0.0027*** (0.0000)	0.0024*** (0.0001)	0.0023*** (0.0002)
Lev	-0.0166*** (0.0000)	-0.0161*** (0.0001)	-0.0178*** (0.0000)	-0.0175*** (0.0000)	-0.0176*** (0.0000)	-0.0176*** (0.0000)	-0.0165*** (0.0001)	-0.0157*** (0.0002)
Cash	-0.0249*** (0.0000)	-0.0248*** (0.0000)	-0.0252*** (0.0000)	-0.0251*** (0.0000)	-0.0243*** (0.0000)	-0.0243*** (0.0000)	-0.0271*** (0.0000)	-0.0262*** (0.0000)
Age	0.0099*** (0.0000)	0.0100*** (0.0000)	0.0103*** (0.0000)	0.0103*** (0.0000)	0.0105*** (0.0000)	0.0105*** (0.0000)	0.0089*** (0.0000)	0.0094*** (0.0000)
Profitability	-0.0575*** (0.0000)	-0.0575*** (0.0000)	-0.0589*** (0.0000)	-0.0587*** (0.0000)	-0.0580*** (0.0000)	-0.0580*** (0.0000)	-0.0585*** (0.0000)	-0.0580*** (0.0000)
Tangibility	-0.0508*** (0.0000)	-0.0509*** (0.0000)	-0.0509*** (0.0000)	-0.0510*** (0.0000)	-0.0508*** (0.0000)	-0.0508*** (0.0000)	-0.0511*** (0.0000)	-0.0511*** (0.0000)
Constant	-0.0761*** (0.0000)	-0.0761*** (0.0000)	-0.0793*** (0.0000)	-0.0779*** (0.0000)	-0.0818*** (0.0000)	-0.0815*** (0.0000)	-0.0682*** (0.0000)	-0.0689*** (0.0000)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.0750	0.0757	0.0745	0.0758	0.0724	0.0726	0.0799	0.0809
Obs	19,072	19,072	19,072	19,072	19,072	19,072	19,072	19,072

Note: This table reports the results of the regression that additionally controls for the firm fixed effect to control for potential endogeneity problem due to differences across firms. Three (3) pledgor types are identified, which include equity pledging by (1) controlling shareholders, (2) non-controlling shareholders, and (3) actual controllers. Each pledgor type is measured using a dummy variable and the pledged ratio by respective pledgor type. The descriptions of the variables are summarized in Table A in the appendix. The superscripts *, **, and *** indicate significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 6: Controlling for lagged effect

	Investment efficiency (*InvEff*)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.D_Controlling	-0.0039***						-0.0056***	
	(0.0000)						(0.0000)	
L.Controlling		-0.0265***						-0.0321***
		(0.0000)						(0.0000)
L.D_Non-controlling			-0.0034***				-0.0064***	
			(0.0021)				(0.0000)	
L.Non-Controlling				-0.0387***				-0.0555***
				(0.0001)				(0.0000)
L.D_Actual					0.0016		0.0042	
					(0.5285)		(0.1106)	
L.Actual Controller						0.0105		0.0852
						(0.8352)		(0.1037)
L.Q	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L.Size	0.0025***	0.0025***	0.0026***	0.0026***	0.0027***	0.0027***	0.0025***	0.0023***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L.Lev	-0.0066**	-0.0059**	-0.0076**	-0.0075**	-0.0076**	-0.0076**	-0.0062**	-0.0055*
	(0.0277)	(0.0469)	(0.0103)	(0.0118)	(0.0113)	(0.0112)	(0.0361)	(0.0645)
L.Cash	-0.0263***	-0.0261***	-0.0266***	-0.0267***	-0.0259***	-0.0260***	-0.0273***	-0.0270***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L.Age	0.0066***	0.0064***	0.0069***	0.0069***	0.0072***	0.0072***	0.0060***	0.0060***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L.Profitability	0.0037	0.0034	0.0027	0.0025	0.0032	0.0032	0.0030	0.0027
	(0.6739)	(0.6922)	(0.7612)	(0.7747)	(0.7163)	(0.7174)	(0.7295)	(0.7604)
L.Tangibility	-0.0321***	-0.0321***	-0.0325***	-0.0326***	-0.0326***	-0.0327***	-0.0316***	-0.0318***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0763***	-0.0744***	-0.0785***	-0.0770***	-0.0803***	-0.0802***	-0.0720***	-0.0694***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.1064	0.1081	0.1057	0.1068	0.1049	0.1049	0.1086	0.1114
Obs	15,284	15,284	15,284	15,284	15,284	15,284	15,284	15,284

Note: This table reports the results of the regression that regress investment efficiency (*InvEff*) on a set of lagged variables. The main independent variables (pledgor type) and control variables are lagged by one-year to control for potential bias due to reverse causality and lagged effect. Three (3) pledgor types are identified, which include equity pledging by (1) controlling shareholders, (2) non-controlling shareholders, and (3) actual controllers. Each pledgor type is measured using a dummy variable and the pledged ratio by respective pledgor type. The descriptions of the variables are summarized in Table A in the appendix. The superscripts *, **, and *** indicate significance at the 90%, 95%, and 99% confidence levels, respectively.

In addition, we add that equity pledges by non-SOEs pledgors hurt investment efficiency more than SOEs-related pledgors (columns 1 and 2 in Table 7). This is because SOEs do not pledge their shares for personal loans and are subject to stricter government monitoring and share-pledging regulation. Furthermore, if the share price crash, it is more complicated to liquidate SOEs pledged shares than for non-SOEs (Pang & Wang, 2020). The findings imply that SOEs-related shareholders have lower incentives to influence corporate policies for personal benefits; instead, they utilize equity pledging as a corporate financing tool.

We also show that SOE-related pledgors can offset the negative impact of equity pledging on investment efficiency. In columns 3 and 5, we interact the pledgor type with dummy SOE. We observe that SOE-related controlling shareholders and actual controllers' pledges enhance investment efficiency. The results are significant at the 1% level, implying that when SOEs hold controlling rights, they can influence corporate decisions in mitigating investment inefficiencies among the pledged firms.

Table 7: SOE-related Pledgor and Investment Efficiency

	InvEff (1)	InvEff (2)	InvEff (3)	InvEff (4)	InvEff (5)
Controlling			-0.0282*** (0.0000)		
Non-Controlling				-0.0478*** (0.0000)	
Actual Controller					-0.1150* (0.0596)
SOE	0.0024 (0.2622)		-0.0009 (0.7877)	0.0038* (0.0934)	0.0022 (0.2981)
Non-SOE		-0.0079*** (0.0000)			
SOE*Controlling			0.0515*** (0.0083)		
SOE*Non-Controlling				-0.0640 (0.3678)	
SOE*Actual Controller					0.3827*** (0.0025)
Q	-0.0016*** (0.0000)	-0.0016*** (0.0000)	-0.0016*** (0.0000)	-0.0017*** (0.0000)	-0.0017*** (0.0000)
Size	0.0023*** (0.0000)	0.0022*** (0.0000)	0.0022*** (0.0000)	0.0023*** (0.0000)	0.0023*** (0.0000)
Lev	-0.0193*** (0.0000)	-0.0182*** (0.0000)	-0.0181*** (0.0000)	-0.0193*** (0.0000)	-0.0193*** (0.0000)
Cash	-0.0266*** (0.0000)	-0.0286*** (0.0000)	-0.0268*** (0.0000)	-0.0274*** (0.0000)	-0.0268*** (0.0000)
Age	0.0098*** (0.0000)	0.0080*** (0.0000)	0.0091*** (0.0000)	0.0095*** (0.0000)	0.0097*** (0.0000)
Profitability	-0.0609*** (0.0000)	-0.0611*** (0.0000)	-0.0607*** (0.0000)	-0.0615*** (0.0000)	-0.0608*** (0.0000)
Tangibility	-0.0566*** (0.0000)	-0.0552*** (0.0000)	-0.0560*** (0.0000)	-0.0564*** (0.0000)	-0.0566*** (0.0000)
Constant	-0.0694*** (0.0000)	-0.0598*** (0.0000)	-0.0650*** (0.0000)	-0.0661*** (0.0000)	-0.0688*** (0.0000)
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Adj R^2	0.1031	0.1094	0.1062	0.1060	0.1034
Obs	19,072	19,072	19,072	19,072	19,072

Note: Columns 1 and 2 report the regression results that account for the differences between state-owned enterprises (SOEs) and non-SOEs related pledgors. SOE is a dummy variable that takes 1 for SOE-related pledgor and 0 otherwise. In columns 3 to 5, SOE interacts with each pledgor type. Three (3) pledgor types are identified, which include equity pledging by (1) controlling shareholders, (2) non-controlling shareholders, and (3) actual controllers. Each pledgor type is measured using the pledged ratio. The descriptions of the variables are summarized in Table A in the appendix. The superscripts *, **, and *** indicate significance at the 90%, 95%, and 99% confidence levels, respectively.

4. Conclusion

Existing studies on equity pledging mostly emphasize the impact of controlling shareholders' pledges on firms. We complement the literature by including the pledgor type in the analysis. The pledgors are divided into controlling shareholders, non-controlling shareholders and actual controllers. Our results show that the negative impact of equity pledges is caused by both the controlling and non-controlling shareholders' pledges. SOEs with controlling rights are found to enhance investment efficiency. To better examine the impact of equity pledges on firms, we recommend that future studies consider the purpose of pledges to capture the pledgors' incentives in making corporate decisions.

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Appendix 1: Variables Description

Variables	Description
InvEff	Absolute value of residuals $\varepsilon_{i,t}$ multiple by -1.
OverInv	Positive residual values, $\varepsilon_{i,t}$
UnderInv	Negative residual values, $\varepsilon_{i,t}$
	Dummy variable equals to 1 for:
D_Pledge	pledge firms.
D_Controlling	controlling shareholders' pledge.
D_Non-controlling	non-controllingshareholders' pledge.
D_Actual	actual controllers' pledge.
Pledge	**Number of new shares pledged over number of shares outstanding.**
Controlling	Pledge ratio of controlling shareholders.
Non-controlling	Pledge ratio of non-controlling shareholders.
Actual	Pledge ratio of actual controller.
SOE	A dummy variable equals to 1 for SOE related pledgor, and 0 otherwise.
Q	Tobin's Q
Size	Natural logarithm of total assets.
Lev	Total debt over total assets.
Cash	Cash and cash equivalent over total assets.
Age	Natural logarithm of firm age from incorporation year.
Profitability	Return on assets
Tangibility	Net property, plant and equipment over total assets.

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COVID-19: PERFORMANCE OF ESG ETFS AND ESG ETFS vs THEIR DECLARED INDEXES

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Abstract

This paper adds knowledge to ESG funds by investigating the performance of 126 ESG ETFs during the Covid-19 market stress. My findings show that ESG ETFs outperform the market during the pandemic, suggesting they are better investment funds. This asserts that ESG funds are more likely to have actual investment performance value than just being marketing tools. In addition, this paper examines whether ESG ETFs attempt to track their indexes exactly, and the results show strong evidence that ETF funds do an excellent job of tracking their indexes they follow before Covid-19, during Covid-19 and Covid-19 recovery. This paper also discusses why ESG funds are more risk-resilient investment tools during a crisis. My findings and discussions aim to inform investors and portfolio managers in decision-making during this outbreak.

JEL: G1, G12, G14, M 14

Keywords: Covid-19, ESG, ETFs, indexes, performance, and ratings

1. Introduction

ESG (environmental, social and governance) funds are growing rapidly. ESG investments are worth over 35 trillion dollars globally in 2020[1]. In the U.S, EGS investments are worth 8.4 trillion dollars at the beginning of 2022[2], and Broadridge Financial Solutions estimates these investments will grow by approximately 30 trillion dollars by 2030[3]. ESG funds are well-known in terms of reducing financial risk, especially during the Covid-19 pandemic. Numerous papers have reported that ESG investments outperform the market during Covid-19, i.e., Albuquerque et al. (2020), Singh (2020), Broadstock et al. (2021), Omura et al. (2021) and Rubbaniy (2021).

As ESG investments become more and more popular, the performance of ESG mutual funds has been studied extensively (Bollen, 2009); Renneboog et al., 2011; Nofsinger & Varma, 2014; Hartzmark & Sussman, (2019). The literature has confirmed the outperformance of mutual funds during the outbreak, suggesting they are more risk-resilient investment tools, i.e., Pastor and Vorsatz (2020), Singh (2020) and Samira et al. (2020). However, studying the performance of ESG ETFs during this pandemic

[1] Source: GSIR-20201.pdf (gsi-alliance.org)
[2] Source: Even as ESG market narrows, money managers in the space prioritize climate | S&P Global Market Intelligence (spglobal.com)
[3] Source: How ESG investment returns are growing as market evolves | Sustainability Magazine

is still scant. There are very few early studies covering the topic of ESG ETFs. For instance, Kanuri (2020) examines the risk and return of ESG ETFs and compares them with investable proxies for U.S. and global equity markets. His finding shows that ESG ETFs underperform compared with others during the period 2005-2019. However, his study is before the Covid-19 pandemic. Following a similar research line but during the Covid-19 outbreak, Folger-Laronde et al. (2020) analysed the difference in the performance of ESG ETFs with different Eco-fund ratings. They find that higher sustainability rating ETFs do not prevent financial losses during the Covid-19 crisis. Their study does not mention the risk resilience of ETFs during the crisis, and it is limited to simple econometrics methods: ANOVA and multivariate regression. On the contrary, Pavlova and De Boyrie (2022) employs numerous econometric models on a sample of 62 sustainable EGS ETFs during the Covid-19 market crash (February- May 2020); they find that sustainability ratings of ESG ETFs do not outperform the market during the crash period, suggesting ESG ETFs are not risk resilient during this outbreak. Their paper is limited to the sample period, which is only halfway through the pandemic, and there are no theories or empirical methods justifying their reason for choosing the Covid-19 period.

This paper investigates the performance of ESG ETFs during Covid-19 market stress by employing five different models: CAPM, Fama-French 3-factor model, Fama-French 3-factor plus a momentum, Fama-French 5-factor model, and Fama-French 5-factor model plus a momentum. Econometric models, including Chow (1960) and Bai-Perron (1998 and 2003), are utilised to justify the appropriate length of the market stress period. By using 126 ESG ETFs from January 2019 to March 2022, my empirical analysis highlights interesting results. First, the findings show that ESG ETFs outperform the market, suggesting ESG ETFs are better investment tools during the pandemic. This paper adds the novel finding of the outperformance of ESG ETFs, which is not reported in the previous literature. Second, it is trustworthy that higher-risk ETFs are associated with better performance. This supports that investors and portfolio managers consider the financial risks while making decisions (Ferriani et al., 2021).

ESG ETFs are purposely created to track their declared indexes exactly. This paper aims to address the question "whether ESG ETFs attempt to track their declared indexes exactly during the Covid-19 market stress". The results show that ESG ETFs do an excellent job of tracking the indexes they follow before Covid-19, during Covid-19 and Covid-19 recovery.

Additionally, this paper explains why ESG funds outperform the market: (1) Investors are loyal to ESG firms, (2) They are optimistic about the future, (3) ESG investors' tastes make firms more valuable, (4) They consider the financial risk while incorporating sustainability and ESG-related decisions into their stock picks.

My paper makes the following major contributions to the extant literature. First, it adds more knowledge on the ESG ETFs, specifically the risk resilience of ESG ETFs during Covid-19. This asserts that ESG funds are more likely to have actual investment performance value than just being marketing tools. Second, this study confirms the outperformance of ESG ETFs funds during the outbreak. There are mixed findings on EGS performance. While Albuquerque et al. (2020), Singh (2020), Broadstock et al. (2021), Omura et al. (2021), and Rubbaniy et al. (2021) document that ESG investments outperform the market during the pandemic, other papers indicate that ESG investments strategies do not pay during Covid-19, including Demers et al. (2021), Takahashi and Yamada (2021) and Pavlova and De Boyrie (2022). Third, lower-rated ETFs (higher-risk ETFs) outperform better than higher-rated ones (lower-risk ETFs), suggesting investors are rewarded more for bearing higher risk. Four, this paper adds novel, strong evidence of the performance of ESG ETFs in tracking their declared indexes before Covid-19, during Covid-10 and Covid-19 recovery. Lastly, my findings and discussions are to inform investors and portfolio managers in the decision-making process, especially during this outbreak.

The paper is organised as follows: Section 2 discusses the data and methodology, section 3 presents the empirical results, and section 4 provides the conclusions.

2. Data and Methodology

2.1. Data

Recent research implicating ESG firm performance during the pandemic has selected different periods of the Covid-19 crisis (Pastor and Vorsatz (2020)[4], Pavlova and De Boyrie (2022)[5], however, their sample periods do not include the Covid-19 continuing periods and are not justified by any theories or econometrics models. This paper follows Chen et al. (2022) to employ two tests: (1) Chow (1960) and (2) Bai and Perron (1998 and 2003) to determine the Covid-19 market stress period. To be consistent with Ferriani et al. (2021) and Pavlova and De Boyrie (2022), ETF funds are separated based on the ratings from Morningstar: the globes variable going from 1 (high ESG risk) to 5 (low EGS risk)[6].

The empirical results are reported in Table 1. Based on the Chow test, all F-statistics are statistically significant, indicating the null hypothesis of no break is rejected. Bai-Perron test shows that ETFs returns change between February 2020 and February 2021. Based on the test results, I define Covid-19 market stress as the period in which ESG ETFs return time series have structural breaks or changes. Therefore, the period from February 2020 to February 2021 is chosen as the period of Covid-19 market stress. Based on this market stress period, the length of the sample is extended and divided into three sub-periods:

(1) Before Covid-19 market distress (January 2019 – January 2020)

(2) During Covid-19 market distress (February 2020 – February 2021)

(3) Covid-19 Recovery (March 2021– March 2022)

U.S ESG ETFs and ESG indexes are collected from Thomson Reuters' Refinitiv database, and accounting data is collected from CRSP during the period January 2019- March 2022. Only ETFs whose ratings are available at Morningstar.com and ETF.com, are included in the sample. There are a total of 126 ESG ETFs and 126 ESG ETF indexes. Fama-French factors are specified on their website[7].

Table 1: Results from Chow and Bai-Perron Tests

	Globes				
	5	4	3	2	1
Panel A: Chow test					
Structural break at observation Feb 1, 2020	28.61***	17.85***	44.92***	36.55***	40.18***
Structural break at observation Feb 28, 2021	19.75***	22.56***	39.19***	20.17***	33.51***
Panel B: Bai -Perron test					
Break Point 1	19/02/2020	20/02/2020	18/02/2020	17/02/2020	20/02/2020
Break Point 2	17/02/2021	15/02/2021	12/02/2021	21/02/2021	22/02/2021

Note: Chow and Bai- Perron tests are employed to determine the Covid-19 market stress period.
ETFs are separated based on the ratings from Morningstar. The globes variable goes from 1 (highest risk) to 5 (lowest risk).
**, **, ** significance at 90%, 95% and 99%, respectively.*

[4] Pastor and Vorsatz (2020) choose Covid-19 pandemic period from Feb 20 to March 23, 2020.
[5] Pavlova and De Boyrie (2022) select Covid-19 crisis period from Feb 20 to May 29, 2020.
[6] Globe variable ratings from 1 to 5 are named by Morningstar as Low, Below Average, Average, Above Average and High sustainability. ETF Investing | Morningstar
[7] Kenneth R. French - Data Library (dartmouth.edu)

2.2. Methodology

Following Pastor and Vorsatz (2020), Luo (2022) and, Pavlova and De Boyrie (2022), I calculate the abnormal return performance of EGS funds by employing five different models:

CAPM:

$$R_t - R_{ft} = \alpha_{BC}D_{BC,t} + \alpha_{DC}D_{DC,t} + \alpha_{CR}D_{CR,t} + \beta_1 * (R_{mt} - R_{ft}) + \varepsilon_t \quad (1)$$

Fama- French 3-factor model:

$$R_t - R_{ft} = \alpha_{BC}D_{BC,t} + \alpha_{DC}D_{DC,t} + \alpha_{CR}D_{CR,t} + \beta_1 * (R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \varepsilon_t \quad (2)$$

Fama-French 3-factor plus a momentum:

$$R_t - R_{ft} = \alpha_{BC}D_{BC,t} + \alpha_{DC}D_{DC,t} + \alpha_{CR}D_{CR,t} + \beta_1 * (R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(WML_t) + \varepsilon_t \ (3)$$

Fama- French 5-factor model:

$$R_t - R_{ft} = \alpha_{BC}D_{BC,t} + \alpha_{DC}D_{DC,t} + \alpha_{CR}D_{CR,t} + \beta_1(R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RML_t) + \beta_5(CMA_t)\ \varepsilon_t \quad (4)$$

Fama- French 5-factor model plus a momentum:

$$R_t - R_{ft} = \alpha_{BC}D_{BC,t} + \alpha_{DC}D_{DC,t} + \alpha_{CR}D_{CR,t} + \beta_1(R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RML_t) + \beta_5(CMA_t) + + \beta_6(WML_t)\ \varepsilon_t \quad (5)$$

Where

R_t: equally weighted return on day t for a group of ETFs from Morningstar (from 1 to 5) or MSCI ESG rating (BB, BBB, A, AA, and AAA)

R_{ft} : risk-free rate

$R_t - R_{ft}$: excess return on the market

$SMB_t, HML_t, RML_t, CMA_t$: size, value, profitability, and investment factors, respectively

WML_t : momentum

$D_{BC,t}$: dummy variable that takes value of 1 before the Covid-19, and 0 otherwise.

$D_{DC,t}$: dummy variable that takes value of 1 during the Covid-19, and 0 otherwise.

$D_{CR,t}$: dummy variable that takes value of 1 during Covid-19 recovery, and 0 otherwise.

T-test for the mean difference in cumulated returns between low and high ESG risk funds.

To be consistent with Elton et al. (2019), when comparing the performance of ESG ETFs vs their indexes, performance is measured in two ways. (1) performance is measured by the difference between the daily return[8] of the fund and the index it follows (in percentage). Then I examine its mean and standard deviation. (2) performance is measured by the daily return of funds against the index by employing three characteristics of regression, including the intercept, the coefficient beta, and the coefficient of determination (R^2).

3. Empirical Results and Discussions

3.1. Descriptive Statistics

Table 2: Summary Statistics of ESG ETF Funds Based on Morningstar Ratings

Number of funds					
Globes	**5**	**4**	**3**	**2**	**1**
Number	7	25	52	28	14
Percentage	6%	20%	41%	22%	11%
Total					126
Daily returns (%)					
Globes	**5**	**4**	**3**	**2**	**1**
Before Covid-19 market distress					
Mean	0.1645	0.1811	0.2173	0.3153	0.3969
Min	-3.1778	-3.364	-5.4819	-3.2591	-4.0178
Max	0.3917	0.5112	0.5726	6.9132	9.0112
St. Dev.	0.1625	0.1709	0.9152	0.8791	1.352
During Covid-19 market stress					
Mean	-0.1672	-0.1822	-0.2103	-0.226	-0.2972
Min	-16.7601	-17.0189	-17.9561	-18.0123	-20.1223
Max	10.1125	10.9726	11.0145	11.9875	15.1125
St. Dev.	3.1179	3.5612	3.9912	4.2215	5.1261
Covid-19 Recovery					
Mean	-0.1212	-0.1299	-0.1778	-0.1821	-0.2217
Min	-11.0123	-12.4516	-12.9861	-14.8717	-16.0126
Max	11.0125	11.9978	13.1197	14.0122	16.1562
St. Dev.	2.1569	2.9785	3.0119	3.9784	4.3351

Note: ETFs are separated based on the ratings from Morningstar. The globes variable goes from 1 (highest risk) to 5 (lowest risk).
Before Covid-19: January 2019 - January, 2020
During Covid-19: February 2020 - February, 2021
Covid-19 Recovery: March 2021 - March, 2022

Table 2 summarizes the descriptive statistics of ESG ETF funds based on Morningstar ratings. The majority of funds belong to Globe 3 (52 funds- 41%), followed by Globe 2 (28 funds-22%), globe 4 (25 funds-20%), globe 1 (14 funds- 11%) and Globe 5 (7 funds-6%). In terms of daily returns, ETFs with higher risk

[8] More details are specified in Elton et al (2019), pp. 267-268.

are associated with greater returns before Covid-19 market distress (0.3969%; 0.3153%; 0.2173%; 0.1811% and 0.1645% for globes 1 to 5, respectively). On the contrary, during Covid-19 crash and Covid-19 recovery, lower-rated ETFs faced more losses than higher-rated ones (i.e., (-0.2972%) for globe 1, (-0.2260%) for globe 2, (-0.2103%) for globe 3, (-0.1822%) for globe 4 and (-0.1672%) for globe 5. This indicates that lower-rated ETFs performed better before the pandemic but suffered more losses during the market crash and Covid-19 recovery.

3.2. Performance of ESG ETFs Based on Ratings

3.2.1. Performance of ESG ETFs Based on Morningstar Ratings

Table 3 results show that overall, ESG ETFs outperform the market during the Covid-19 since all alphas are positive and significant (i.e., 0.0412 for globe 5, 0.0511 for globes 4, 0.0578 for globe 3, 0.0591 for globe 2 and 0.0601 for globe 1 in model (1); 0.0325 for globe 5, 0.0356 for globe 4, 0.0416 for globe 3, 0.0455 for globe 2 and 0.0478 for globe 1 in model (2)), suggesting ESG ETFs are better investment tools during this pandemic. This novel finding adds additional information to the decision-making process for investors and portfolio managers.

In addition, ETFs with higher risk are associated with better performance[9], for instance, alpha in globe 1 is higher than alphas in globes 2, 3, 4 and 5 in model (1) (0.0601 for globe 1 vs 0.0591 for globe 2, 0.0578 for globe 3, 0.0511 for globe 4 and 0.0412 for globe 5). My results relate to the findings of Albuquerque et al. (2020), Pastor and Vorsatz (2020), Singh (2020), Broadstock et al. (2021), Omura et al. (2021), Rubbaniy et al. (2021) and Pavlova and De Boyrie (2022). This indicates that investors and portfolio managers take into account the financial risks when making decisions, which is consistent with Ferriani et al. (2021) that risk has been significantly considered during the Covid-19 crisis. Higher risk is rewarded with greater return. There is no clear observation on the performance of ESG ETFs before Covid-19 and during Covid-19 recovery since most of the alphas are not statistically significant except for alphas in globe 1 and globe 2 in model (5) before Covid-19 market stress (0.0623 for globe 1 and 0.0521 for globe 2).

3.2.2. Performance of ESG ETF Based on MSCI Ratings

For a robust test, ETF funds are separated based on the ratings Morgan Stanley Capital International (MSCI): rating variables include BB, BBB, A, AA, AAA[10]. Table 4 results confirm the outperformance of ESG ETFs during the pandemic since all alphas are positive and significant, for instance, 0.0451 for AAA funds, 0.0497 for AA funds, 0.0512 for A funds, 0.0522 for BBB funds and 0.0534 for BB funds in model (1); 0.0325 for AAA funds, 0.0391 for AA funds, 0.0411 for A funds, 0.0432 for BBB funds and 0.0451 for BB funds in model (2). Additionally, the results are consistent with Morningstar ratings that lower-rated ETFs outperform better than higher-rated ones[11] (i.e., 0.0534 for BB funds vs 0.0522 for BBB funds, 0.0512 for A funds, 0.0391 for AA funds and 0.0325 for AAA funds in model (1)). There is no indication regarding ETFs performance before Covid-19 and Covid-19 recovery because most alphas are not statistically significant.

[9] T-tests are also performed to test the mean difference in cumulated returns between low and high ESG risk funds, and the results are not reported here but support that lower-rated funds perform better than higher-rated ones.

[10] MSCI ratings include BB, A, AA, and AAA that are rated by Morgan Stanley Capital International. ESG Investing: ESG Ratings - MSCI

[11] T-tests are also performed to test the mean difference in cumulated returns between low and high ESG risk funds, and the results are not reported here but support that lower-rated funds perform better than higher-rated ones.

Table 3: Performance of ESG ETFs Based on Morningstar Ratings

Globes	Period	Alpha (%) -1	-2	-3	-4
5	Before Covid-19	0.0097	0.0875	0.0529	0.0674
		-2.01	-1.75	-2.11	-1.55
	During Covid-19	0.0412**	0.0325**	0.0293**	0.0212**
		-2.75	-2.11	-2.55	-2.12
	Covid-19 Recovery	-0.0178	-0.0356	0.0526	0.0425
		(-1.55)	(-2.16)	-1.78	-1.82
4	Before Covid-19	-0.0716	0.0267	0.0356	-0.0762
		(-1.78)	-1.54	-1.98	(-2.11)
	During Covid-19	0.0511***	0.0356**	0.0319**	0.0279**
		-3.42	-2.67	-2.58	-2.69
	Covid-19 Recovery	0.0789	-0.0345	0.054	0.0751
		-1.34	(-1.54)	-1.56	-1.17
3	Before Covid-19	0.0672	0.0871	0.0245	0.0512
		-1.82	-1.88	-1.24	-1.78
	During Covid-19	0.0578**	0.0416**	0.0342**	0.0305**
		-2.64	-2.75	-2.87	-2.71
	Covid-19 Recovery	-0.0234	-0.0324	0.0234	0.0532
		(-1.05)	(-1.23)	-1.26	-1.53
2	Before Covid-19	0.0657	0.0871	0.0234	0.0219
		-1.16	-1.56	-1.22	-1.25
	During Covid-19	0.0591**	0.0455**	0.0387**	0.0329**
		-2.85	-2.72	-2.55	-2.51
	Covid-19 Recovery	0.0452	0.0215	-0.0326	0.0213
		-1.21	-1.62	(-1.39)	-1.7
1	Before Covid-19	0.0412	0.0516	0.0718	0.0212
		-1.23	-1.55	-1.29	-1.38
	During Covid-19	0.0601***	0.0478**	0.0412**	0.0355**
		-3.56	-2.85	-2.47	-2.22
	Covid-19 Recovery	0.0345	0.0616	0.0413	0.0214
		-1.31	-1.18	-1.52	-1.78

Note: Alphas are measured by five different models: (1) CAMP, (2) FF- 3 factors, (3) FF- 3-factor plus a momentum, (4) FF-5 factors and (5) FF- 5 factors plus a momentum.
**, **, ** significance at 90%, 95% and 99%, respectively.*
T-statistics are in parentheses.

Table 4: Performance of ESG ETFs Based on Morningstar Ratings

MSCI Ratings	Period	Alpha (%)			
		-1	-2	-3	-4
AAA	Before Covid-19	0.0124	0.0316	0.0524	0.0623
		-1.75	-1.11	-1.56	-1.21
	During Covid-19	0.0451**	0.0325**	0.0213**	0.0356**
		-2.77	-2.54	-2.2	-2.81
	Covid-19 Recovery	0.0125	0.0314	0.0512	0.0612
		-1.29	-1.67	-1.12	-1.78
AA	Before Covid-19	0.0425	0.0523	0.0312	0.0425
		-1.32	-1.52	-1.29	-1.1
	During Covid-19	0.0497***	0.0391**	0.0311**	0.0397**
		-3.37	-2.89	-2.75	-2.58
	Covid-19 Recovery	-0.0234	-0.0123	0.0432	0.0612
		(-1.99)	(-1.22)	-1.83	-1.44
A	Before Covid-19	-0.0123	0.0123	0.0456	0.0532
		(-1.15)	-1.77	-1.27	-2.01
	During Covid-19	0.0512**	0.0411**	0.0356**	0.0412*
		-2.82	-2.85	-2.77	-2.01
	Covid-19 Recovery	0.0167	0.0678	0.0189	0.0542
		-1.26	-1.42	-1.76	-1.22
BBB	Before Covid-19	0.0617	0.0425	-0.0123	0.0432
		-1.33	-1.12	-1.74	-1.55
	During Covid-19	0.0522*	0.0432**	0.0398*	0.0433**
		-2.07	-2.25	-2.05	-2.97
	Covid-19 Recovery	-0.0425	0.0234	0.0126	0.0723
		(-1.16)	-1.11	-1.24	-1.72
BB	Before Covid-19	0.0321	0.0524	0.0412	0.0748
		-1.05	-1.98	-1.78	-1.67
	During Covid-19	0.0534**	0.0451**	0.0411**	0.0467*
		-2.26	-2.75	-2.58	-2.02
	Covid-19 Recovery	0.0345	0.0652	0.0312	0.0422
		-1.13	-2.12	-1.67	-1.32

Note: Alphas are measured by five different models: (1) CAMP, (2) FF- 3 factors, (3) FF- 3-factor plus a momentum, (4) FF-5 factors and (5) FF- 5 factors plus a momentum.
ETFs are divided based on MSCI ratings.
**, **, ** significance at 90%, 95% and 99%, respectively.*
T- statistics are in parentheses.

Once again, ETFs outperform the market, suggesting the risk resilience of ESG ETFs during this outbreak. This supports the idea that ESG funds are more likely to have an actual investment performance value than just being marketing tools.

3.3. Performance of ESG ETFs vs their Indexes

Table 5 represents the performance of ESG ETFs, and their declared indexes as discussed above. The results show that ETFs have a higher return than the indexes they follow (mean = 0.0019%, 0.0017% and 0.0015% before Covid-19, during Covid-19 and Covid-19 recovery, respectively, in column 1) [12]. On the second measurement of performance based on time series regression, the coefficient beta is exactly 1 and significant before Covid-19, during Covid-19 and Covid-19 recovery (column 4), which indicates that ETFs do an excellent job of tracking their declared indexes, and ESG ETFs remain true to ESG principles before the Covid-19, during Covid-19 and Covid-19 recovery. This adds novel and strong evidence of the excellent job of ETFs in tracking their declared indexes during three periods.

Table 5: Difference in Return of ETFs vs. their Indexes and Regression Results

Period	Mean (%) -1	Std. Dev. (%) -2	Intercept -3	Beta -4	R^2 -5
Before Covid-19	0.0019	0.0179	0.0028	1** -2.85	0.9989
During Covid-19	0.0017	0.0301	0.0037	1** -2.52	0.9981
Covid-19 Recovery	0.0015	0.0175	0.0019	1** -2.64	0.9985

Note: (1): indicate the average daily return difference between ESG ETFs and the indexes they follow. (2): indicate the standard deviation of the daily return difference between ESG ETFs and the indexes they follow. (3), (4) and (5): represent the intercept, coefficient beta and from time series regression of return for ETFs against the indexes they follow.
**, **, ** significance at 90%, 95% and 99%, respectively.*
T- statistics are in parentheses.

3.4. Discussions

Why ESG funds outperform the market during Covid-19 market stress can be explained in four ways. First, investors are loyal to ESG firms. Albuquerque et al. (2019) and Albuquerque et al. (2020) assert that investor loyalty plays an important role in the performance of ESG funds; specifically, their loyalty to ESG firms is to benefit ESG firms' stock performance and resiliency. Albuquerque et al. (2019) provide the benefit of product differentiation strategy that investors are more loyal and more subjective to lower price-elasticity of demand for their ESG funds/stocks. A lower price-elastic demand allows the firm to charge higher prices and have higher profit margins that lead to lower operating leverage, thus lower systematic risk and increasing firm value. Following the same line, Albuquerque et al. (2020) developed a different strategy based on advertising expenditures to measure investor loyalty to ESG firms during Covid-19. They find that high advertising expenditures are associated with high customer loyalty. In addition, stock return is more pronounced for firms with high advertising expenditures, suggesting firm performance and resilience are associated with investor loyalty during the pandemic.

Second, investors are optimistic about the future of sustainable funds. Pastor et al. (2020) find that investors retain their commitments to sustainability during the COVID-19 crisis, suggesting they are optimistic about the future. Their findings indicate that investors have considered sustainable funds necessities rather than luxury goods. Third, ESG investors' tastes make firms more valuable. Pastor et al. (2021) report that ESG investors' tastes affect the relative performance of green and brown firms[13];

[12] T- test are performed to test the mean difference of the daily return between ETFs and their indexes for three periods: before, during Covid-19 and Covid-19 recovery. The results are not reported here but show that there is a significant difference in their daily return between ETFs and their index for all three periods.

[13] "Green firms" generate positive externalities for society while "brown firms" impose negative externalities.

specifically, they boost green firm values while hurting brown ones. Their results show that investor tastes for green holdings affect asset prices. They are willing to pay more for greener firms, thereby lowering the firms' costs of capital and increasing the firm value compared to brown ones. Lastly, investors consider the financial risk while incorporating sustainability and ESG-related decisions into their stock picks. Ferriani et al. (2021) report that risk has been significantly considered in investor decision-making, especially during the Covid-19 crisis.

4. Conclusions

The Covid-19 pandemic has had tremendous impacts on the investment areas. This paper aims to contribute to the literature by first investigating the performance of ESG ETFs during Covid-19 market stress. The results show that ETF funds outperform the market, suggesting ESG ETFs are more risk-resilient investment tools during this outbreak. This also indicates that ESG ETFs are not merely marketing tools but instead provide the actual investment value. In addition, higher rating ESG funds are associated with better performance, supporting that bearing higher risk may be rewarded with greater return. Second, this paper examines whether ESG ETFs track their declared indexes exactly during this market distress. The findings show that ETFs do an excellent job of tracking their declared indexes before Covid-19, during Covid-19 and Covid-19 recovery with high R^2 (0.9989, 0.9981 and 0.9985, respectively). My paper adds clear evidence of the excellent job of ESG ETFs in tracking their indexes they follow. Lastly, this paper provides a discussion on why ESG funds outperform the market during this pandemic. My findings and discussions aim to inform investors and portfolio managers in decision-making during this Covid-19 market stress.

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TOWARDS A SIMPLIFIED CAN SLIM MODEL

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Abstract

AAII.com ranks four stock-picking models by Buffet, Graham, Greenblatt, and O'Neil (CAN SLIM) that consistently outperform the S&P 500. Implementing these models requires complicated procedures that an average investor might find challenging. Also, the website does not identify the companies comprising each portfolio or provide statistical analyses. We show how even an unskilled investor can implement these models. Given that AAII.com ranks CAN SLIM the best, coupled with the observed popularity of this model among practitioners and student investment funds, we offer a simpler version of the model, which too consistently outperforms the S&P 500.

1. Introduction

The efficient capital market theory suggests that it is impossible to consistently beat the market portfolio by picking stocks based on publicly available information: the most obvious implication is that if one cannot beat the market portfolio, one might as well join it. Despite the market efficiency, a few "Wizards" have consistently outperformed the market (usually, the S&P 500 Index). Warren Buffet, Benjamin Graham, Joel Greenblatt, and William O'Neil (CAN SLIM) fall in this distinguished group. None of these individuals is privy to the inside information of the firms they hold in their portfolio. So, their extraordinary success must be owing to their unique stock-picking acumen.

The margins of victory of the models over the S&P 500 have varied from one wizard to another. The American Association of Individual Investors (AAII.com), among others, has studied the relative efficiency of the four models. The stock screen on AAII.com gives real-time results of passing companies and breaks down the criteria from the books published on the famous investor model[1]. The website provides the reader with a list of criteria and then displays the results without the ability to replicate them.[2] The first objective of this paper is to show how ordinary investors can use these models with relative ease to compare their efficiencies.

The CAN SLIM appears to be the best-performing Wizard strategy on the AAII stock screen. Also, the CAN SLIM system has been widely used among practitioners and student investment funds.[3] Despite

[1] For example, Jack Schwager, Market Wizards, 1989 New York Institute of Finance.

[2] When filtering forward, the screen shows the returns over the last three or five years or one year but does not show the passing companies and does not allow for statistical analysis.

[3] CAN SLIM's parent company, Investor's Business Daily, which the Wall Street Journal recently acquired, publishes a list of the top 50 (IBD 50) following the CAN SLIM criteria. The list has claimed to beat the market over the last several years and has become so popular that it is now an exchange-traded fund (ETF). Furthermore, student funds have found success using the model. For example, the College of Business at East Carolina University ran a study using the CAN SLIM system and beat the

the popularity of CAN SLIM, an average investor will likely find its execution difficult. Our second objective is to propose a much friendlier and shorter version of the model, the Adjusted CAN SLIM method (hereinafter, ACS). Our work will help make implementing these models easier to average investors, student-managed funds, and smaller institutions using tools for under $100 a month.[4]

The paper proceeds along the following lines. Section II describes the four Wizard models as well as the ACS method we propose. We discuss the methodology in Section III and the results in Section IV. Section V concludes.

2. Details of the Four Models

2.1 CAN SLIM

The CAN SLIM acronym is discussed in the book O'Neil (2002, 1995). The letters stand for the investing criteria such as current quarterly earnings (C), annual earnings (A), new products, new management, new highs (N), supply and demand (S), leader, or laggard (L), institutional sponsorship (I), market direction (M).

The system breaks down individual criteria for each letter in the acronym and how it should relate to buying stock. The "C" and "A" letters refer to quarterly and annual growth rates; the higher, the better. "N" stands for catalysts for growth or momentum. "S" refers to quarterly or annual sales growth (the higher, the better) or supply and demand, such as buying stocks with high relative strength. "L" stands for the position of stock within the industry and the industry's position in the market. The goal is to buy leading stocks in leading industries. "I" stands for institutional sponsorship, large pension fund, and institutional investing. This would refer to following smart money or large shareholders. "M" stands for market direction and means to buy when the market is in an uptrend or expansion period. These are all challenging criteria to screen for and automate, which makes replication and simulation difficult for academic study. After meeting the above fundamental and checklist criteria, the study also looks for stocks from O'Neil proper chart bases.

In summary, the CAN SLIM system recommends making investment decisions not purely based on momentum but focusing on stocks with innovative products, services, and ideas, from properly timed chart patterns, with explosive growth in earnings and before their price is run up[5]. According to O'Neil, no one in their right mind buys stocks that have gone through excessive price increases following extreme relative strength.

2.2 Graham

Benjamin Graham illustrates the method for value investing initially described in 1949. In addition, several publications further elaborate on the technique.[6] Graham describes buying growth stocks as stocks with steady track records of increasing earnings per share (EPS) and high earnings per share well above the norm for common stock. This is related to the CAN SLIM method of investing but is too

market from 1998 to 2005.[3] The College of Business at the University of Southern California (USC) also uses the CAN SLIM method by trading the IBD 50. North Coast Asset Management (northcoast.com) manages a CAN SLIM portfolio which is, to our knowledge, the only investment fund created around a famous investor strategy.

[4] It's $84/month using portfolio123.com backtest.

[5] The hand-collected analysis of CAN SLIM founder Bill O'Neil shows stocks improve 100% or more after meeting the CAN SLIM criteria.

[6] They include the one by Warren Buffet in the 1976 edition of Financial Analyst Journal titled "Benjamin Graham." Further, Buffet explains investing strategies of Graham and Doddsville in "The Superinvestors of Graham-and-Doddsville."

risky for defensive investing. Graham discusses buying common stock as buying in low markets and selling in high markets, finding bargain issues, selectively choosing growth stocks, and buying special situations. This sounds relatable and is similar to CAN SLIM.

The Enterprising Investor model suggested by Graham is more relatable to the CAN SLIM method and involves buying bargain companies with a long dividend track record and strong earnings stability. The strategy aims to find low price-earnings (P/E) ratio stocks. This is something the CAN SLIM method ignores but is critical to Graham. These stocks are considered bargains. Graham also discusses finding stocks with robust financial conditions. This involves picking stocks with a current ratio of at least 1.5 and long-term debt no higher than 100% of current assets. Graham recommends stocks with at least a 5-year track record of positive earnings for earnings per share. Lastly, Graham recommends buying stocks with a Price-to-Book-ratio (P/B) of 120% of tangible book value.

3.3 Buffett

Buffet's methodology is somewhat similar to Graham's. The Buffet factors include a strong uptrend in earnings per share, high return on equity, high sustainable earnings per share, low debt to assets compared to the industry, net profit margin and net operating margin better than the industry, and better return on equity than the industry.

3.4 Greenblatt

Greenblatt is famous for the 'Magic Formula' of investing. The formula is based on two sorts, one for value and another for quality. The purpose is to find quality companies that are undervalued. Stocks are selected with the following characteristics: liquid stocks not trading on the over the counter (OTC) market, a market cap of at least $50 million, no ADR stocks (the U.S. only), no financial companies, utility companies, or Real Estate Investment Trusts (REITS), and high values of 5-year return on investment. Appendix I details each strategy, the definition of the variable, and the corresponding code for replication based on Portfolio123.com.

We make additional efforts to make implementing these models friendlier. First, we remove limiting factors that would cause the model to hold only a few stocks at a time and give volatile results. For example, the Buffet model's screening process includes a strong uptrend in earnings per share, high return on equity, high sustainable earnings per share, low debt to assets compared to the industry, net profit margin, and net operating margin better than the industry, and better return on equity than the industry. We modify the Buffet model requirements to a) the stocks being in the top 75% of earnings per share (EPS) compared to the industry, b) EPS better than the last three years compared with the last seven, and c) EPS having grown within the past year and past seven years. Appendix II provides the details of such modifications. Second, to help investors better understand some of the technical words used in this paper, we provide a list of glossaries in Appendix III.

3. Methodology

3.1 Procedure

Following AAII's back-testing procedure, we scan each month for the list of passing stocks and carry the portfolio for the next trading day[7]. We use data from the fact set to screen for the positions and plug in the criteria for screening through a portfolio management tool from portfolio123.com, which uses point-in-time data from FactSet. We combine the rules from AAII.com with what is already in

[7] We take the positions at the average of the next trading day's high, low, and 2x close and incur no carrying cost or transaction costs.

portfolio123.com for implementing the four models. We follow the steps prescribed by each 'Wizard'- Buffet, Graham, O'Neil, and Greenblatt and compare their performances.[8]

For benchmarking purposes, we select annual return, total return, standard deviation (for risk measurement), Sharpe ratio (for risk-adjusted returns), and alpha and beta. These are commonly used benchmarking measures (Neely et al., 2014).

AAII.COM's 'Wizard' model site suggests buying stocks that pass a fundamental filter each month and dropping stocks from their portfolio that no longer pass the filter. This is known as rebalancing. For each of our famous investor models, we modify the number of filters to aggregate any difference between the AAII.com website, the books from the famous investor models, and the screening tool from portfolio123.com (see Appendix II)[9].

According to AAII.com, the CAN SLIM model performs best over the January 1998 – March 2023 sample period. We shorten their sample period to match the maximum data available from Portfolio123.com (January 1999-March2023). Shortening their sample involves recomputing the total return for each model by downloading the data and recomputing the cumulative return across the new sample. Doing this leads to a slightly different ranking of the models. For example, their site for the new sample shows that Graham outperforms the CAN SLIM model. Our sample consistently gives CAN SLIM the top ranking.

4. Results

We report the results in the two sub-sections below. In the first section, we compare the efficiency of models relative to each other and the INDEX portfolio—the four models discussed above. The second section explains the adjusted CAN SLIM model (ACS) and compares its results with the S&P500 index.

For a fee, AAII.com produces a list of the passing stocks from each screen. There are no legal issues with producing the information on a paid or free document.

4.1 Comparing the Wizards

Figure 1 depicts the models' performances (including the market index) over the period from January 2, 1999, through March 2023. All models begin with an original investment of $100 (000's). All four Wizard models overwhelmingly outperform the market index. In terms of performance ranking, CAN SLIM is at the forefront with the ending portfolio value of $16,601.55, with Buffet being the second ($7,173.34) and the third being nearly tied between Graham ($1,583.81) and Greenblatt ($1,367.08).

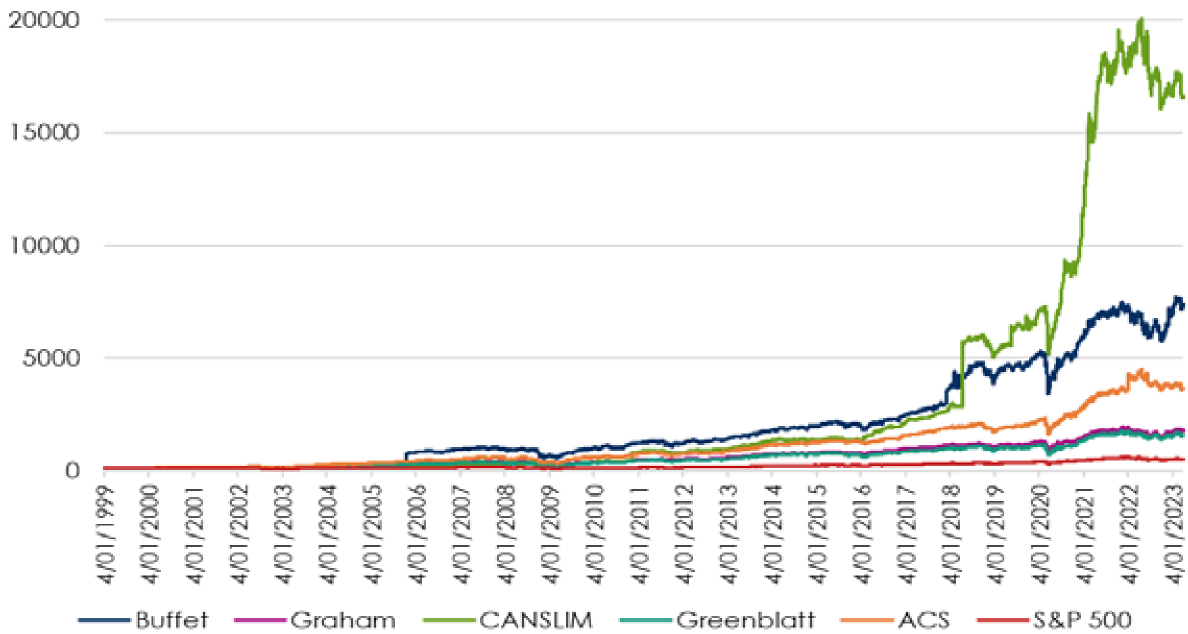
Table 1 compares five models, four Wizard models, and the S&P 500 across several performance measures. In addition to annualized returns, the table provides Sharpe Ratio and alpha and beta; Max Drawdown is defined as the lowest peak to trough on the equity curve, and Sharpe Ratio stands for the return from the investment over the treasury bill divided by the investment standard deviation. CAN SLIM ranks as the best performer among the five models. CAN SLIM has the highest annualized returns. In addition, it has the highest alpha along with the lowest beta.

Although CAN SLIM ranks the best, the full implementation of the model is still complicated for an average investor. To simplify the CAN SLIM strategy further, we suggest an adjusted CAN SLIM method

[8] Investors that want to implement the screen in real-time would buy the list of passing companies and rebalance monthly.
[9] AAII does not consider transaction costs. We do not either.

(ACS) for such investors. We do not expect the ACS model to perform as well as the fully executed CAN SLIM model. We will consider the ACS model successful if it can beat the S&P 500.

Figure 1: Famous Investor Growth Models



Note: The Figure charts the investment growth of four Wizard models and the S&P 500 from January 2, 1999, to March 30, 2023. The starting investment in each portfolio is $100.00.

Table 1: Comparing Efficiencies

	Buffet	Graham	CAN SLIM	GREENBLATT	S&P 500
Total Return	7273.14%	1683.81%	16550.93%	1472.21%	405.10%
Annualized Return	19.42%	12.63%	23.50%	12.04%	6.91%
Max Drawdown	-49.44%	-51.84%	-55.08%	-56.77%	-55.19%
Sharpe	0.60	0.73	0.76	0.63	0.39
Std Dev	33.19%	15.94%	30.62%	18.66%	15.41%
Beta	0.80	0.90	0.69	1.08	1.00
Alpha	16.04%	6.46%	20.99%	5.31%	0.00%

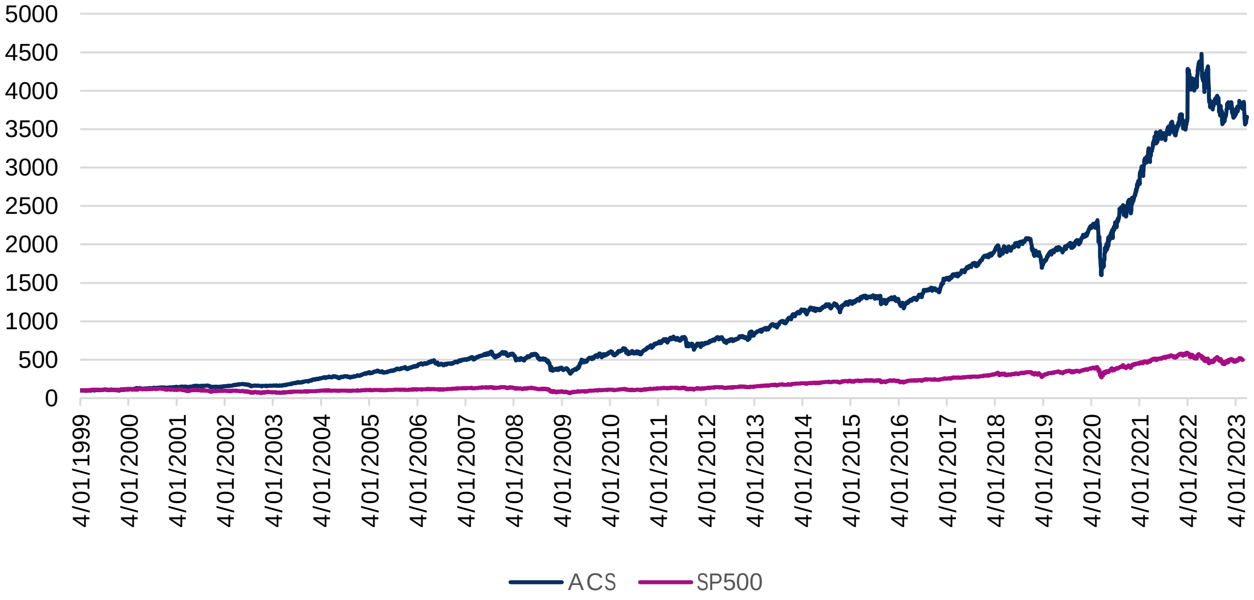
Note: This table compares five models, four Wizard models, and the S&P 500 across several performance measures. Max Drawdown is the lowest return from peak to trough, and Sharpe Ratio is the excess return divided by the standard deviation. Alpha and beta are excess return and slope coefficients on the regression of the stock returns explained by the market return.

4.2 The ACS Model

We simplify the CAN SLIM model by using only the factors related to price and earnings per share. While it seeks to mimic the full-scale CAN SLIM model results, the ACS model relies only on a simple small-scale version of the key component factors of CAN SLIM (earnings and price). We call it the ACS model because it is the acronym for adjusted CAN SLIM (A C S). Appendix III provides details of the ACS model. We do not provide a shortened version of other models, but it would be an interesting avenue for future work.

Figure 2 portrays the performances of the ACS model versus the S&P 500 and testifies to the consistent superiority of the ACS model.

Figure 2: Returns on S&P 500 and the ACS Model



Note: The Figure charts the investment growth of the ACS model and the S&P 500 from January 2, 1999, to March 30, 2023. The starting investment in each portfolio is $100.00.

Table 2 is similar in construction to Table 1 and compares the ACS model with the S&P 500 across several performance measures. The results show that, from January 1999 through March 2023, the ACS portfolio earned a 3,558.48% return compared to the S&P 500's 405.10%. Additionally, the ACS portfolio has a lower beta and higher alpha than the market index. Thus, Figure 2 and Table 2 confirm the superiority of the ACS model to the market index.

Table 2: Comparing Performances: ACS vs. S&P 500

	ACS	S&P 500
Total Return	3558.48%	405.10%
Annualized Return	16.01%	6.91%
Max Drawdown	-47.01%	-55.19%
Sharpe	0.97	0.39
Std Dev	15.04%	15.41%
Beta	0.71	1
Alpha	10.87%	0.00%

Note: This table compares the ACS and S&P 500 models across several performance measures. Max Drawdown is the lowest return from peak to trough, and Sharpe Ratio is the excess return divided by the standard deviation. Alpha and beta are excess return and slope coefficients on the regression of the stock returns explained by the market return.

5. Conclusions

The efficient capital market theory suggests that it is not possible to consistently beat the market portfolio by picking stocks based on publicly available information. However, a few "Wizards" have consistently outperformed the market (specifically, the S&P 500 Index). Warren Buffet, Benjamin Graham, Joel Greenblatt, and William O'Neil fall into this distinguished group. None of these individuals is privy to the inside information of the firms they hold in their portfolio. So, their extraordinary success must be owing to their unique stock-picking acumen.

AAII.com, the official website of the American Association of Individual Investors, implements these models based on the criteria espoused by the wizards and provides real-time results on their performances (i.e., the last five-, three-, and one-year returns). An average investor is likely to find replicating these models rather tricky. In addition, the website does not identify the companies comprising each portfolio or provide statistical analyses. This paper demonstrates how ordinary investors can use these Wizard models relatively easily.

Upon analyzing the four models, AAII.com places O'Neil's CAN SLIM model at the top. Our analyses of these models also arrive at the same conclusion. The observed superior performance of CAN SLIM has contributed to its popularity among practitioners and student investment funds. This model, however, requires several steps that might be difficult for average investors to execute, thus prompting us to suggest and implement a shorter and friendlier model, which we call Adjusted CAN SLIM (ACS). We demonstrate that the ACS model consistently outperforms S&P500. The procedures outlined in this paper will be helpful for individuals who want to manage their portfolios with limited time, expertise, and resources.

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Appendices

Appendix 1. Four Wizards' Stock Screening Models

MODEL	STEPS		DEFINITION OF VARIABLES	PORTFOLIO 123.COM
Buffet	1	Stocks in the top 75% of EPS compared to the industry.	EPS Excluding Extraordinary Items is earnings per share, including all-expense except those deemed extraordinary.	Frank("EPSExclXorGr%5Y",#industry)>25
	2	Annual EPS has been better in the last three years than the last 7.	Growth=Earnings Per Share value taken straight out of the SEC filing with the most recent three-year and 7-year values. The 3-year value is the average growth over the last three years, and the seven years is t.	EPSExclXor(2,ann)>=EPSExclXor(6,ann)
	3	EPS grew over the past year and the past seven years.	EPS Growth Last year = % Change in EPS from the previous year. EPS Growth in the last Seven years is a %Change in EPS from 7 years ago.	EPSExclXor(0,ann)>EPSExclXor(1,ann)
	4	ROE last 12 months better than the industry median	ROE = Return on Equity divided by the Average Common Equity as a percentage. Average Common Equity is the average of the Common Equity at the beginning and the end of the period. Median = The trailing 12-month return compared to the median of the industry	EPSExclXor(0,ann)>EPSExclXor(6,ann)
	5	ROE 5 year-average better than the industry	Average ROE = each year's ROE for the last five years added and divided by five. The industry is value for each stock trading in the same industry.	ROE%5YAvg>FMedian("ROE%5YAvg",#industry)
	6	Sustainable growth rate in the top 15% compared to industry peers.	Sustainable Growth = Trailing twelve-month Retention Rate multiplied by the trailing twelve-month Return on Equity, divided by 100.	Frank("SusGr%",#industry)>85
	7	Debt to equity lower than the industry	Debt To Equity = Total Debt divided by Total Common Equity for the same period.	DbtTot2EqQ <= DbtTot2EqQInd
	8	Net profit margin higher than the industry	Net Profit Margin (NPM) = NPM divided by Total Revenue for the period expressed as a percentage above value for industry value	NPMgn%TTM >= NPMgn%TTMInd
	9	Operating profit margin higher than the industry	Operating Profit Margin = percent of revenues remaining after paying all operating expenses. It is calculated as operating Income divided by Total Revenue	OpMgn%TTM >= OpMgn%TTMInd

MODEL	STEPS		DEFINITION OF VARIABLES	PORTFOLIO 123.COM
Graham	1	No thinly traded over-the-counter (OTC) stocks. Choose more liquid stocks.	Over the Counter = Least liquid stocks.	Universe(NOOTC)
	2	Current ratio is at least 1.5	Current Ratio = Total Current Assets divided by Total Current Liabilities for the same period.	CurRatioQ>=1.5
	3	Long-term debt is less than 110% of working capital.	Long-term debt = All debt that is due more than 12 months after the date of the latest balance sheet,	DbtLTQ<=(CurAstQ- CurLiabQ)*1.10
	4	Last four quarters of EPS positive	Positive EPS = EPS above 0 for each of the last four quarters	EPSExclXor(0,qtr)>0 and EPSExclXor(1,qtr)>0 and EPSExclXor(2,qtr)>0 and EPSExclXor(3,qtr)>0

	5	Last five years of EPS positive	Positive EPS = EPS above 0 for each of the last 5 years.	EPSExclXor(0,ann)>0and EPSExclXor(1,ann)>0 and EPSExclXor(2,ann)>0 and EPSExclXor(3,ann)>0 and EPSExclXor(4,ann)>0
	6	Annual EPS grew over the past year and past five years.	EPS Growth = EPS this year above last year's and 5 years ago.	EPSExclXor(0,ann)>EPSExclXor(1,ann) andEPSExclXor(0,ann)>EPSExclXor(4,ann)
	7	Company has paid dividends within the past year	Dividends = Dividends per share in the previous year.	DivPSTTM>0
MODEL		**STEPS**	**DEFINITION OF VARIABLES**	**PORTFOLIO 123.COM**
CAN SLIM	1	Percentile rank for % institutional ownership between 10 and 50	Percentile Rank = Percent of Institutional Ownership in relation to other stocks in the universe. Institutional Ownership is the number of institutional investors, including large firms and pension funds, who buy the stock.	Frank(" Inst%Own",#all,#desc)>=10 and Frank(" Inst%Own",#all,#desc)<50
	2	EPS growth (latest qtr.) Percentile rank in top 35%	Percentile Rank = EPS growth within the top 35% of available stocks	Frank(" EPSExclXorGr%PYQ")>=65
	3	Share price % gain in last 240 trading days ranks in the top 35%	Share Price Gain = Share Price Percent Gain in the top 35% of available stocks over roughly last year.	Frank("Close(0)/Close(240)")>=65
	4	Distance between the current price and the 12-month high ranks in top 50%	Distance = Current price is within the top 50% of stocks trading near their 12-month high.	5. Frank(" Price/ PriceH")>=50
MODEL		**STEPS**	**DEFINITION OF VARIABLES**	**PORTFOLIO 123.COM**
Greenblatt	1	Choose liquid stocks not trading over the counter (OTC).	Over the Counter = Least liquid stocks.	Universe(NOOTC)
	2	Market cap is at least $50 million.	Market Cap = Share Price x Shares Outstanding.	MktCap>=50
	3	U.S. stocks only, no ADR	Non-U.S. companies = American Depository Receipts (foreign companies trading on a U.S. exchange)	Universe($ADR)=false
	4	No financial or utility companies or REITs	Financial sector, Utility Sector, Real estate Investment Trusts	!GICS(FINANC) and !GICS(UTILIT) and !GICS(reoper)
	5	5-year return on investment is in the top 35%	Return on Investment = This value is the trailing twelve-month Income After Taxes divided by the average total long-term debt and Stockholder's Equity, expressed as a percentage.	Frank(" ROI%5YAvg")>=65
MODEL		**STEPS**	**DEFINITION OF VARIABLES**	**PORTFOLIO 123.COM**
ACS Model	1	EPS growth is above 15% 5-year average, and EPS growth is above 25% in the most recent quarter compared to the same quarter one year prior.	EPS Growth 5-year average is each year added over the last five years divided by five, equal to 15% or more. The most recent quarter is this quarter's EPS divided by the same quarter last year minus one above 25%.	EPSExclXorGr%5Y>=15And EPSExclXorGr%PQ > 25
	2	Price is within 10% of a new high	High is stock price all-time high. The price is the current price.	Price >= 0.9 * PriceH

Appendix II. Modification of the filters employed at AAII.com.

MODEL		AAII.COM	OUR MODIFICATION
BUFFETT	1	Market capitalization (price * shares outstanding) of greater than or equal to 1 billion dollars.	No minimum cutoff market capitalization
	2	Positive operating income for the trailing twelve months and each of the last seven years	Not considered
	3	ROE greater than 15%	Return on equity over the last 12 months (also last five years) is better than the industry median.
	4	Current operating profit margin greater than the industry's current median operating margin	The current operating profit margin greater than that of the industry over the last year.
	5	The current net profit margin exceeds the industry's median operating profit margin.	Net profit margin better than the industry's median last year.
	6	Low price to free cash flows	Not considered
	7	EPS growth over the last year and seven years; a sustainable growth rate within the top 15% of the industry peers.	Not considered
MODEL		**AAII.COM**	**OUR MODIFICATION**
GRAHAM	1	Price-earnings ratio among the lowest 25%	Not considered
	2	Firms that intend to pay a dividend next year	Firms that paid a dividend last year
	3	EPS for the last 12 months is more significant than the previous five years.	EPS growth over the last 12 months and last five years
MODEL		**AAII.COM**	**OUR MODIFICATION**
CAN SLIM	1	Buy stocks with earnings per share up at least 20% in the most recent quarter compared to the same quarter one year prior.	EPS growth in the latest quarter is in the top 35% of available stocks
	2	Buy stocks with a growth rate in earnings in the most recent quarter and the same quarter one year prior greater than the growth rate in earnings between two quarters ago and the same quarter one year prior.	Not considered
	3	Buy stocks with a growth rate in sales of at least 25% in the most recent quarter compared to the same quarter one year prior.	Not considered
	4	Buy stocks with EPS from continuing operations for the latest quarter greater than zero.	Not considered
	5	Buy stocks with EPS from operations in the last 12 months greater than earnings per share for the previous year.	Not considered
	6	Buy stocks with earnings per share from continuing operations for the last year greater than earnings per share from operations two years ago.	Not considered
	7	Buy stocks with earnings per share growing more two years ago than three years ago and earnings growing three years ago more than four years ago.	Not considered
	8	By stocks with consensus earnings for the current year greater than diluted earnings for the last year.	Not considered
	9	By stocks with a three-year average growth rate greater than or equal to 25%.	Not considered

MODEL		AAII.COM	OUR MODIFICATION
	10	Buy stocks that have relative strength over 52 weeks greater than 80	Not considered
	11	Buy firms with at least ten institutional shareholders.	Not considered
	12	Buy firms where the number of shares purchased by institutions over the last quarter is greater than or equal to the number sold over the previous quarter.	The percentage of institutional ownership is between 10 and 50 percent.
MODEL		**AAII.COM**	**OUR MODIFICATION**
GREENBLATT	1	Buy stocks with EBIT/EV above the risk-free rate. The higher, the better.	Not considered
	2	The higher the return on invested capital, the better the investment	We buy the top 35% of companies ranked by return on invested capital.
	3	Minimum market cap between 50 million and 5 billion	We use a cutoff of 50 million for the market cap
	4	Rank stocks on return on capital (highest to lowest)	Not considered
	5	Next, rank on the ratio of EBIT to EV (highest to lowest)	Not considered
	6	Buy 20 to 30 stocks by purchasing five to seven every few months.	We buy all passing stocks.
	7	Hold for one year	We rebalance monthly

Appendix III. Glossary

Term	Definition
ADR	American Depository Receipts
Backtesting	Backtesting involves following the historical buy and sells rules with data as it occurred at that point in time and recording the performance.
Chart Bases	Chart bases include a pattern, such as a trading range breakout, that would signal a low-risk entry to buy the stock.
Chart Patterns	Chart patterns include double bottom and inverse head and shoulders (see Lo et al. 2000).
Double Bottom	A chart pattern indicating a reversal in stock prices from a selloff. The pattern involves a decline, rebound, another decile to a similar level, and a final rebound to end the falling of stock prices.
Equity Curve	The equity curve involves the plotting of a real money investment (e.g., growth of $1) from investing in the fund returns.
High Relative Strength	Stocks that have been advancing by more than the market or have a high accumulation rating or a large number of funds flowing into the stock.
Index	INDEX is the S&P 500 Index and is used as our benchmark for success
Special Situations	The payout is independent of stock market factors and is a one-time event.

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HIGH-FREQUENCY TRANSACTION DATA: A COMPARISON BETWEEN TWO ASYMMETRIC MODELS

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Abstract

This paper compares two asymmetric models for high-frequency transaction data in financial markets, namely, the three-state Asymmetric Autoregressive Conditional Duration (AACD) model and the Activity Direction Size (ADS) model. It is shown that the two asymmetric models measure different aspects of the same underlying asymmetric nature of high-frequency transaction data. It is also shown that by extending the AACD model to include two size variables and adjusting for partial durations, each model's parameter estimates can be used to estimate the other model's parameters exactly. Thus, the two asymmetric models are equivalent, and measure the durations and price changes jointly.

Keywords: High-frequency transaction data

JEL: G15

1. Introduction

High-frequency transaction data in financial markets occurs in continuous time and is irregularly spaced. Models of high-frequency transaction data measure the durations and/or price changes of security. Some models focus on the inter-arrival times (durations) between high-frequency transactions and other models focus on the changes in the price of the security of interest. For example, by far the most common class of models for measuring the inter-arrival times between transactions is the class of Autoregressive Conditional Duration (ACD) models (Bauwens & Hautsch, 2009). More generally, it has been shown that durations and price changes can be modelled jointly as a marked point process (see Engle, 2000). As the number of models of high-frequency transaction data increases, it is important to reflect on the similarities of current models. The motivation of this paper is to highlight the underlying commonalities between two asymmetric models of high-frequency transaction data, namely, the Activity Direction Size (ADS) model (Rydberg and Shephard, 2003) and the three-state Asymmetric Autoregressive Conditional Duration (AACD) model (Tay et al., 2011). The three-state asymmetric autoregressive conditional duration is a generalisation of the Autoregressive Conditional Duration (ACD) model of Engle and Russell (1998). Thus, by comparing two generalised asymmetric models, such as the ADS model and the three-state AACD, further comparisons can be made to more specific models of high-frequency transaction data.

The Activity Direction Size (ADS) model decomposes high-frequency scaled price movements of a security into three main variables, namely, activity, direction, and size

(Rydberg and Shephard, 2003). For each transaction, *activity* measures whether the price moved (active) or was flat (inactive). Conditional on the price moving, *direction* measures whether the price moved up or down. Also conditional on the price moving, *size* measures the magnitude of the move in multiples of tick sizes. The ADS model captures the asymmetry between up and down price movements through both direction and size.

Inter-arrival times (durations) between transactions are usually modelled with conditional duration models, with the most well-known model being the Autoregressive Conditional Duration (ACD) model of Engle and Russell (1998). A two-state Asymmetric Autoregressive Conditional Duration (AACD) model of Bauwens and Giot (2003) extended the ACD model by including two durations, namely, up durations and down durations. In addition, a three-state Asymmetric Autoregressive Conditional Duration (AACD) of Tay et al. (2011) extended the two-state AACD model by including three durations, namely, flat durations, up durations, and down durations. Extensive surveys on conditional duration models demonstrate that it is an active area of research (see Pacurar, 2008; Bhogal and Ramanathan, 2019).

In this paper, the three-state AACD model is extended to mirror the two size variables of the ADS model, namely, an *up size* and a *down size*. In addition, by incorporating partial durations, this paper contributes to the literature by showing that each model's parameter estimates can be used to estimate the other model's parameters exactly. Thus, the two asymmetric models are equivalent and measure different aspects of the same asymmetric model. Ultimately, the two asymmetric models measure the durations and price changes jointly, which demonstrates that both models are more general than originally expected.

2. Material and Methods

2.1 Preliminaries

High-frequency transaction data in financial markets occurs in continuous time and is irregularly spaced. For example, when a transaction occurs, a price, a volume, and a time are recorded. Models of high-frequency transaction data measure both the durations and price movements of a security. More specifically, the price of a security within a specified time period can be written as:

$$P_{t_e} = P_{t_i} + \sum_{n=1}^{N} \Delta P_{t_n} \tag{1}$$

where P_{t_e} is the price of the security at the *end time* t_e, P_{t_i} is the price of the security at the *initial time* t_i, ΔP_{t_n} is the change in the price of the security between times t_n and t_{n-1}, t_n is the transaction's arrival time, and N is the number of transactions, with $t_i \leq t_1 \leq \cdots \leq t_n \leq \cdots \leq t_N \leq t_e$.

The prices are discrete and live on a lattice of prices driven by the tick size of the security (Rydberg and Shephard, 2003). The scaled price of a security at time t_n can be written as:

$$Z_{t_n} = P_{t_n}/\kappa \tag{2}$$

where Z_{t_n} is the *scaled price*, P_{t_n} is the price, and κ is the *tick size*. The tick size scales the price to be an integer lattice of scaled prices. In addition, the change in the scaled price of a security at time t_n can be written as:

$$
\begin{aligned}
\Delta Z_{t_n} &= Z_{t_n} - Z_{t_{n-1}} \\
&= P_{t_n}/\kappa - P_{t_{n-1}}/\kappa \\
&= \Delta P_{t_n}/\kappa
\end{aligned} \tag{3}
$$

where ΔZ_{t_n} is the change in the scaled price, ΔP_{t_n} is the change in the price with $\Delta P_{t_n} = P_{t_n} - P_{t_{n-1}}$, and κ is the tick size.

2.2 Partial Durations

Partial duration represents the time-interval (duration) between the end time and the last transaction time. For example, the total elapsed time can be written as:

$$T = t_e - t_i \tag{4}$$

where T is the *total time*, t_i is the initial time, and t_e is the end time. The *duration* (inter-arrival time) between two transactions is given by:

$$\Delta t_n = t_n - t_{n-1} \tag{5}$$

where Δt_n is the duration, t_n and t_{n-1} are transaction arrival times. The *expected unadjusted duration* can be estimated by:

$$
\begin{aligned}
\psi &= \tfrac{1}{N}\textstyle\sum_{n=1}^{N} \Delta t_n \\
&= \tfrac{1}{N}(t_N - t_i) \\
&= \tfrac{T_N}{N}
\end{aligned} \tag{6}
$$

where ψ is the expected unadjusted duration, Δt_n is the duration in Equation (5), $T_N = (t_N - t_i)$ and N is the number of transactions.

However, if a transaction doesn't occur at the end time, there exists a *partial duration*, which is the time since the last transaction at time t_N. The partial duration is given by:

$$\delta = t_e - t_N \tag{7}$$

where δ is the *partial duration*, t_N is the last transaction time, and t_e is the end time. Incorporating the partial duration into the expected duration estimation in Equation (6) produces:

$$
\begin{aligned}
\psi^* &= \tfrac{1}{N}\delta + \psi \\
&= \tfrac{1}{N}\delta + \tfrac{T_N}{N} \\
&= \tfrac{T_N}{N}
\end{aligned} \tag{8}
$$

where ψ^* is the expected *adjusted duration*, δ is the partial duration in Equation (7), ψ is the expected *unadjusted duration* in Equation (6), Δt_n is the duration in Equation (5), and T is the total time in Equation (3), with:

$$T = \delta + \textstyle\sum_{n=1}^{N} \Delta t_n$$

$$= t_e - t_i \tag{9}$$

When N is large, the partial duration δ plays a small role in the calculation of the expected duration in Equation (8), since:

$$\lim_{N \to \infty} \frac{1}{N} \delta = 0 \tag{10}$$

However, the partial duration plays an important role when comparing the two asymmetric models.

Assuming that the arrival times of transactions are exponentially distributed, the expected intensity is estimated by:

$$\begin{aligned} \lambda &= \frac{1}{\psi^*} \\ &= \frac{N}{T} \end{aligned} \tag{11}$$

where λ is the expected adjusted intensity, ψ^* is the expected adjusted duration in Equation (8), N is the number of transactions, and T is the total time in Equation (9).

2.3 Activity Direction Size (ADS) Model

The Activity Direction Size (ADS) decomposition of the change in the *scaled* price of a security at time t_n can be written as:

$$\Delta Z_{t_n} = A_{t_n} D_{t_n} S_{t_n} \tag{12}$$

where ΔZ_{t_n} is the change in the scaled price in Equation (3), A_{t_n} is the *activity*, D_{t_n} is the *direction*, and S_{t_n} is the *size* (Rydberg and Shephard, 2003).

The *activity* of a security represents whether a transaction moves the price or not. The probability that transactions are active (moves the price) can be estimated by:

$$\begin{aligned} p(A = 1) &= \tfrac{1}{N} \textstyle\sum_{n=1}^{N} I(A_{t_n} = 1) \\ &= \tfrac{N_A}{N} \end{aligned} \tag{13}$$

where $p(A = 1)$ is the probability that transactions are active, A_{t_n} is the *activity* of the transaction price at time t_n, $I(A_{t_n} = 1)$ an indicator variable that is one when a transaction moves the price and zero otherwise; and N_A is the number of transactions where the price moved, with $N_A = \sum_{n=1}^{N} I(A_{t_n} = 1)$. In contrast, the probability that transactions are *flat* (not active) can be estimated by:

$$
\begin{aligned}
p(A = 0) &= 1 - p(A = 1) \\
&= 1 - \tfrac{N_A}{N} \\
&= \tfrac{N_F}{N}
\end{aligned}
\qquad (14)
$$

where $p(A = 0)$ is the probability that transactions are flat, $p(A = 1)$ is the probability that transactions are active in Equation (13), N_F is the number of flat transactions, N_A is the number of active transactions, and N is the total number of transactions, with $N = N_F + N_A$.

The *up direction* of a security represents whether a transaction moved the price up or not. The conditional probability for the up direction is given by:

$$
\begin{aligned}
p(D = 1|A = 1) &= \tfrac{1}{N_A}\textstyle\sum_{a=1}^{N_A} I(D_{t_a} = 1) \\
&= \tfrac{N_U}{N_A}
\end{aligned}
\qquad (15)
$$

where $p(D = 1|A = 1)$ is the conditional probability that active transactions move the price up, D_{t_a} is the *direction* of the transaction price at time t_n, $I(D_{t_n} = 1)$ an indicator variable that is one when the price moves up and zero otherwise. Similarly, the *down direction* of a security represents whether a transaction moved the price up or not. The conditional probability for the down direction is given by:

$$
\begin{aligned}
p(D = -1|A = 1) &= \tfrac{1}{N_A}\textstyle\sum_{a=1}^{N_A} I(D_{t_a} = -1) \\
&= \tfrac{N_D}{N_A}
\end{aligned}
\qquad (16)
$$

where $p(D = -1|A = 1)$ is the conditional probability that active transactions move the price down, D_{t_a} is the *direction* of the transaction price at time t_n, $I(D_{t_n} = -1)$ an indicator variable that is one when the price moves down and zero otherwise, and $N_A = N_U + N_D$ with:

$$p(D = 1|A = 1) + p(D = -1|A = 1) = 1 \qquad (17)$$

Finally, the *size* of a security represents the magnitude of the price movement in multiples of tick sizes. Assuming information asymmetry between the magnitude of the up and down movements, *size* is usually separated into *up size* and *down size*. Typically, there is no *flat size*, as the conditional probability for flat size is given by:

$$p(S_F = 0|A = 0) = 1 \qquad (18)$$

where $p(S_F = 0|A = 0)$ is the conditional probability that flat transactions do not move the price, which is one. The conditional probabilities for *up size* and *down size* are given by:

$$p(S_U = z|D = 1, A = 1) \qquad (19)$$

$$p(S_D = z|D = -1, A = 1) \qquad (20)$$

where $p(S_U = z|D = 1, A = 1)$ is the conditional probability that up transactions move the price up by z tick sizes, and $p(S_D = z|D = -1, A = 1)$ is the conditional probability that down transactions move the price down by z tick sizes.

Table 1 reports the ADS model for different values (z) of the scaled price change. The expected value of the change in the scaled price is given by:

$$
\begin{aligned}
E(\Delta Z) &= p(A=0)E(S_F) + p(A=1)p(D=1|A=1)E(S_U) - p(A=1)p(D=-1|A=1)E(S_D) \\
&= w_U E(S_U) - w_D E(S_D) \qquad (21)
\end{aligned}
$$

where $E(\Delta Z)$ is the expected change in the scaled price of the security, $E(S_F)$ is the expected *flat size*, $E(S_U)$ is the expected *up size*, $E(S_D)$ is the expected *down size*, $w_U = p(A=1)p(D=1|A=1)$ is the up weight, and $w_D = p(A=1)p(D=-1|A=1)$ is the down weight. The $E(S_F) = 0$ since by definition there is no price movement for flat transactions.

Table 1: Activity Direction Size (ADS) Model

States	z	$p(\Delta Z_{t_n} = z)$	Weights
Flat	$z = 0$	w_F	$w_F = p(A=0)$
Up	$z = 1,2,..$	$w_U p(S_U = z)$	$w_U = p(A=1)p(D=1\|A=1)$
Down	$z = -1,-2,..$	$w_D p(S_D = z)$	$w_D = p(A=1)p(D=-1\|A=1)$

Notes: Table 1 reports the ADS model for different values (z) of the scaled price change with: $p(A=0)$ is the probability of *flat* transactions, $p(A=1)$ is the probability of *active* transactions, $p(D=1|A=1)$ is the conditional probability that *active* transactions move the price up, $p(D=-1|A=1)$ is the conditional probability that *active* transactions move the price down, w_F is the *flat* weight, w_U is the *up* weight, w_D is the *down* weight, $p(S_U = z)$ is the probability of an *up size* transaction equalling z, and $p(S_D = z)$ is the probability of a *down size* transaction equalling z.

2.4 Asymmetric Autoregressive Conditional Duration with Size (AACDS)

Inter-arrival times (durations) between transactions are typically modelled with conditional duration models, such as the Autoregressive Conditional Duration (ACD) model of Engle and Russell (1998). The three-state AACD model of Tay et al. (2011) extended the two-state AACD of Bauwens and Giot (2003) to include three durations, namely, *flat durations* (*F*), *up durations* (*U*), and *down durations* (*D*).

A size variable was not included in the original three-state AACD model, as less than 0.5% of the transactions moved more than one tick (Tay et al., 2011). However, in this paper, two size variables are included in the three-state AACD model to mirror the size variables of the ADS model, namely, an *up size* and a *down size*. The extended three-state AACD with size model will be referred to as the *three-state AACDS model*.

The standard ACD model can be written in terms of a marked point process (see Engle, 2000). In this context, the *three-state AACDS model* can be written as three marked point processes by:

$$
\begin{aligned}
p(\psi_F^*, S_F) &= p(\psi_F^*)p(S_F|\psi_F^*) = p(\psi_F^*) \\
p(\psi_U^*, S_U) &= p(\psi_U^*)p(S_U|\psi_U^*) \qquad (22) \\
p(\psi_D^*, S_D) &= p(\psi_D^*)p(S_D|\psi_D^*)
\end{aligned}
$$

where $p(\psi_F^*, S_F)$, $p(\psi_U^*, S_U)$, and $p(\psi_D^*, S_D)$ are joint probability distributions of the associated adjusted durations and scaled price changes for flat transactions, up transactions, down transactions, respectively. All flat size movements are equal to zero, so that $p(S_F = 0|\psi_F^*) = 1$.

Using Equation (8), the expected adjusted duration for the three states can be written as:

$$\psi_F^* = \frac{T}{N_F} \quad \psi_U^* = \frac{T}{N_U} \quad \psi_D^* = \frac{T}{N_D} \tag{23}$$

where ψ_F^* is the expected adjusted *flat* duration for N_F flat durations, ψ_U^* is the expected adjusted *up* duration for N_U up durations, ψ_D^* is the expected adjusted *down* duration for N_D down durations, and T is the total time in Equation (9).

Assuming that the arrival times of the transactions of the three states are exponentially distributed and using Equation (11), the expected intensities are estimated by:

$$\lambda_F = \frac{1}{\psi_F^*} = \frac{N_F}{T} \quad \lambda_U = \frac{1}{\psi_U^*} = \frac{N_U}{T} \quad \lambda_D = \frac{1}{\psi_D^*} = \frac{N_D}{T} \tag{24}$$

where λ_F is the expected *flat intensity*, λ_U is the expected *up intensity*, λ_D is the expected *down intensity*, and the other terms are from Equation (23). The expected intensity for all transactions can be estimated by:

$$\begin{aligned} \lambda &= \lambda_F + \lambda_U + \lambda_D \\ &= \frac{1}{T}(N_F + N_U + N_D) \\ &= \frac{N}{T} \\ &= \frac{1}{\psi^*} \end{aligned} \tag{25}$$

where λ is the expected intensity of all N transactions, with $N = N_F + N_U + N_D$, ψ^* is the expected *adjusted duration*, and the other terms are from Equation (23) and Equation (24).

Table 2 reports the AACDS model for different values (z) of the change in the scaled price. The expected value of the scaled price change can be written as:

$$\begin{aligned} E(\Delta Z) &= \frac{\lambda_F}{\lambda_F+\lambda_U+\lambda_D}E(S_F) + \frac{\lambda_U}{\lambda_F+\lambda_U+\lambda_D}E(S_U) - \frac{\lambda_D}{\lambda_F+\lambda_U+\lambda_D}E(S_D) \\ &= w_F E(S_F) + w_U E(S_U) - w_D E(S_D) \\ &= w_U E(S_U) - w_D E(S_D) \end{aligned} \tag{26}$$

where $E(\Delta Z)$ is the expected change in the scaled price of the security, $E(S_F)$ is the expected *flat size*, $E(S_U)$ is the expected *up size*, $E(S_D)$ is the expected *down size*, $w_F = \frac{\lambda_F}{\lambda_F+\lambda_U+\lambda_D}$ is the flat weight, $w_U = \frac{\lambda_U}{\lambda_F+\lambda_U+\lambda_D}$ is the up weight, and $w_D = \frac{\lambda_D}{\lambda_F+\lambda_U+\lambda_D}$ is the down weight. The $E(S_F) = 0$ since by definition there is no price movement for flat transactions.

Table 2: Three-state AACDS Model

States	z	$p(\Delta Z_{t_n} = z)$	Weights
Flat	$z = 0$	w_F	$w_F = \frac{\lambda_F}{\lambda_F+\lambda_U+\lambda_D}$
Up	$z = 1,2,..$	$w_U p(S_U = z)$	$w_U = \frac{\lambda_U}{\lambda_F+\lambda_U+\lambda_D}$
Down	$z = -1,-2,..$	$w_D p(S_D = z)$	$w_D = \frac{\lambda_D}{\lambda_F+\lambda_U+\lambda_D}$

Notes: Table 2 reports the AACDS model for different values (z) of the change in the scaled price with: λ_F is the *flat* (or *inactive*) intensity, λ_A is the total number of *active* intensity, λ_U is the *up* intensity, λ_D is the *down* intensity, w_F is the *flat* weight, w_U is the *up* weight, w_D is the *down* weight, $p(S_U = z)$ is the probability of an *up size* transaction equalling z, and $p(S_D = z)$ is the probability of a *down size* transaction equalling z.

2.5 Comparison

In this section, it is shown that the estimated parameters of each asymmetric model can be used to estimate the parameters of the other model. It is also shown that if the partial durations are used, the models are identical. The three-state Asymmetric Autoregressive Conditional Duration with Size (AACDS) model consists of three durations (flat, up, and down) and two size variables (up and down). The ADS model consists of two indicator variables (activity and direction) and two size variables (up and down).

The probabilities associated with the activity and direction of the ADS model can be written in terms of both the expected adjusted durations and the expected intensities of the three-state AACDS model by:

$$p(A = 0) = \frac{N_F}{N} = \frac{N_F}{T}\frac{T}{N} = \frac{\psi^*}{\psi_F^*} = \frac{\lambda_F}{\lambda} \tag{27}$$

$$p(A = 1) = \frac{N_A}{N} = \frac{N_A}{T}\frac{T}{N} = \frac{\psi^*}{\psi_A^*} = \frac{\lambda_A}{\lambda} \tag{28}$$

$$p(D = 1|A = 1) = \frac{N_U}{N_A} = \frac{N_U}{T}\frac{T}{N_A} = \frac{\psi_A^*}{\psi_U^*} = \frac{\lambda_U}{\lambda_A} \tag{29}$$

$$p(D = -1|A = 1) = \frac{N_D}{N_A} = \frac{N_D}{T}\frac{T}{N_A} = \frac{\psi_A^*}{\psi_D^*} = \frac{\lambda_D}{\lambda_A} \tag{30}$$

where $\psi_A^* = \frac{T}{N_A}$ is the expected adjusted *active* duration for $N_A = N_U + N_D$ active durations, $\lambda_A = \frac{N_A}{T} = \frac{1}{\psi_A^*}$ is the expected *active intensity*, and all other terms have been previously described. Thus, the estimated parameters of the three-state AACDS model can be used to estimate the parameters of the ADS model.

Similarly, the three expected intensities of the three-state AACDS can be written in terms of the estimated probabilities of the ADS model by:

$$\lambda_F = \frac{N_F}{T} = \frac{N_F}{N}\frac{N}{T} = \frac{N}{T}p(A = 0) \tag{31}$$

$$\lambda_U = \frac{N_U}{T} = \frac{N_U}{N}\frac{N}{T} = \frac{N}{T}p(A = 1)p(D = 1|A = 1) \tag{32}$$

$$\lambda_D = \frac{N_D}{T} = \frac{N_D}{N}\frac{N}{T} = \frac{N}{T}p(A = 1)p(D = -1|A = 1) \tag{33}$$

where all terms have been previously described. Thus, the estimated parameters of the ADS model can be used to estimate the parameters of the three-state AACDS model. It should be noted that because all duration models account for partial durations, the common total time (T) makes the two asymmetric models equivalent.

Table 3: Comparison of the two asymmetric models

States	z	$p(\Delta Z_{t_n} = z)$	ADS Weights	AACDS Weights
Flat	$z = 0$	w_F	$w_F = p(A = 0)$	$w_F = \frac{\lambda_F}{\lambda_F+\lambda_U+\lambda_D}$
Up	$z = 1,2,..$	$w_U p(S_U = z)$	$w_U = p(A = 1)p(D = 1\|A = 1)$	$w_U = \frac{\lambda_U}{\lambda_F+\lambda_U+\lambda_D}$
Down	$z = -1,-2,..$	$w_D p(S_D = z)$	$w_D = p(A = 1)p(D = -1\|A = 1)$	$w_D = \frac{\lambda_D}{\lambda_F+\lambda_U+\lambda_D}$

Notes: Table 3 reports both the ADS and the AACDS model for different values (z) of the scaled price change with: $p(A = 0)$ is the probability of *flat* transactions, $p(A = 1)$ is the probability of *active* transactions, $p(D = 1|A = 1)$ is the conditional probability that *active* transactions move the price up, $p(D = -1|A = 1)$ is the conditional probability that *active* transactions move the price down, λ_F is the *flat* (or *inactive*) intensity, λ_A is the total number of *active* intensity, λ_U is the *up* intensity, λ_D is the *down* intensity, w_F is the *flat* weight, w_U is the *up* weight, w_D is the *down* weight, $p(S_U = z)$ is the probability of an *up size* transaction equalling z, and $p(S_D = z)$ is the probability of a *down size* transaction equalling z.

In general, the expectation of the scaled change in price for both models can be written as:

$$\begin{aligned} E(\Delta Z) &= w_F E(S_F) + w_U E(S_U) - w_D E(S_D) \\ &= w_U E(S_U) - w_D E(S_D) \end{aligned} \tag{34}$$

where $E(\Delta Z)$ is the expected change in the scaled price of the security, $E(S_F)$ is the expected *flat size*, $E(S_U)$ is the expected *up size*, and $E(S_D)$ is the expected *down size*. The $E(S_F) = 0$ since by definition there is no price movement for flat transactions.

2.6 Predictive (conditional) models

It should be noted that more sophisticated dynamic models are typically used to estimate both asymmetric models. In this paper, both asymmetric models have been described as simple in-sample models. Models can be estimated *contemporaneously* (in-sample) or *predictively* (out-of-sample). In addition, most applications of both asymmetric markets have been used for predictions. For example, the joint probability function at time t_n for a are *predictive* model can be written as:

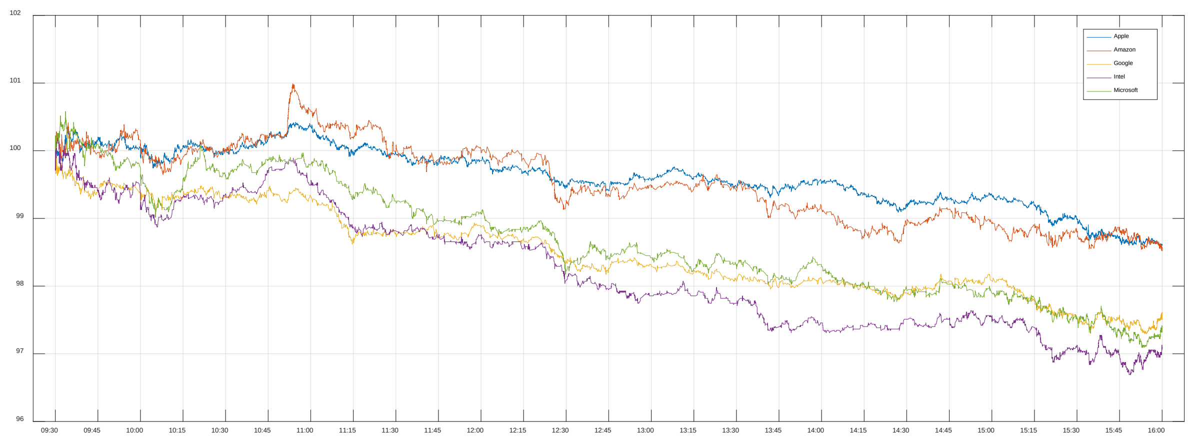
$$p(\psi_{t_n}, S_{t_n} | \mathcal{F}_{t_{n-1}}) \tag{35}$$

where ψ_n is the duration, S_{t_n} is the size, and all explanatory variables used in the model exist in the *filtration* $\mathcal{F}_{t_{n-1}}$: past *information*. However, the motivation of this paper is to compare the variables of the two asymmetric models, rather than focus on any particular version of the models.

3. Results

The data sample of transaction prices is a single day (21st June 2012) sourced from Lobster for five US securities, namely, Apple, Amazon, Google, Intel, and Microsoft. Figure 1 displays the prices rebased at 100. All securities depreciated over the day, where the depreciations were -1.38% for Apple, -1.48% for Amazon, -2.42% for Google, -2.94% for Intel, and -2.66% for Microsoft.

Figure 1: Security prices rebased at 100



Notes: Figure 1 displays the transaction prices for the 21st of June, 2012 for the five securities, namely, Apple, Amazon, Google, Intel, and Microsoft.

Table 4 reports summary statistics of the high-frequency transaction data for the prices of the five securities. The tick size κ for all five securities is 0.005. The total time T for all five securities is 23,400 seconds (6.5 hours). The securities with the three highest number of transactions are: Apple at 34,990, Microsoft at 33,414, and Intel at 32,483. In contrast, the securities with the two lowest number of transactions are: Amazon at 11,419 and Google at 11,678. Interesting, both Intel and Microsoft have a large number of transactions that do not move the price with 29,693 from 32,483 and 30,218 from 33,414, respectively.

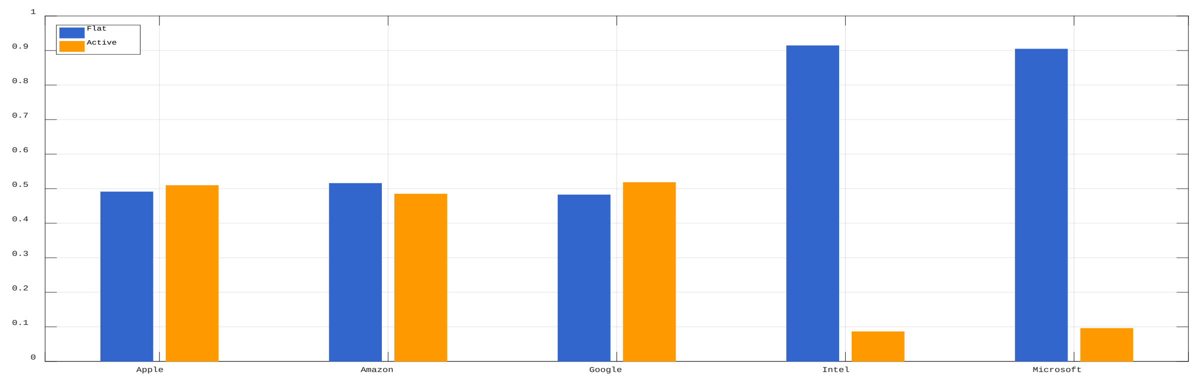
Table 4: Summary Statistics of the Security Prices

	Apple	Amazon	Google	Intel	Microsoft
κ	0.005	0.005	0.005	0.005	0.005
T	23,400	23,400	23,400	23,400	23,400
N	34,990	11,419	11,678	32,483	33,414
N_F	17,175	5,886	5,631	29,693	30,218
N_A	17,815	5,533	6,047	2,790	3,196
N_U	8,948	2,921	2,973	1,397	1,545
N_D	8,867	2,612	3,074	1,393	1,651

Notes: Table 4 reports the summary statistics of the high-frequency transaction data for the prices of the five securities, which consists of: κ is the tick size, T is the total time, N is the total number of transactions, N_F is the total number of *flat* (or *inactive*) transactions, N_A is the total number of *active* transactions, N_U is the total number of *up* transactions, and N_D is the total number of *down* transactions.

Table 5 reports the parameter estimates of the Activity Direction Size (ADS) model. Figure 2 displays the activity of the transaction prices, displaying both the probability of flat transaction prices ($p(A = 0)$) and the probability of active transaction prices ($p(A = 1)$). Intel and Microsoft both have high probabilities for flat transaction prices with values of 0.914 and 0.904. Thus, over 90% of the transactions associated with Intel and Microsoft do not move the price. In contrast, the conditional probability for both directions are all close to 0.500. For example, the largest conditional probability difference of 0.056 is for Amazon, which has a conditional probability of an up direction of 0.528 compared to a conditional probability of a downward direction of 0.472. The size variables are common to both asymmetric models and will be discussed later.

Figure 2: Activity Probabilities



Notes: Figure 2 displays the activity of the transaction prices for the 21st of June, 2012 for the five securities, namely, Apple, Amazon, Google, Intel, and Microsoft. *Flat* represents the probability of flat transaction prices and *Active* represents the probability active transaction prices.

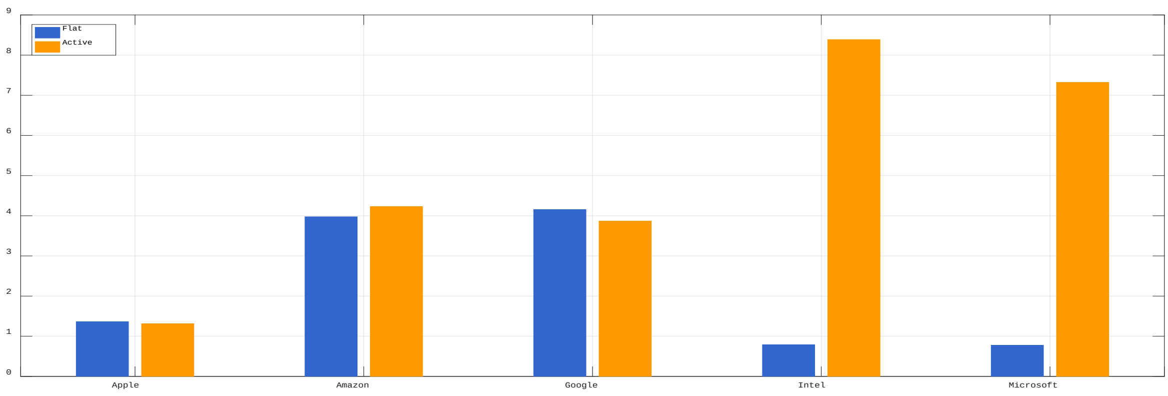
Table 5: Activity Direction Size (ADS) model

	Apple	Amazon	Google	Intel	Microsoft
$p(A=0)$	0.491	0.516	0.482	0.914	0.904
$p(A=1)$	0.509	0.485	0.518	0.086	0.096
$p(D=1\|A=1)$	0.502	0.528	0.492	0.501	0.483
$p(D=-1\|A=1)$	0.498	0.472	0.508	0.499	0.517
S_U	6.537	6.045	10.747	1.395	1.548
S_D	6.780	7.013	11.308	1.515	1.548

Notes: Table 5 reports the parameter estimates of the Activity Direction Size (ADS) model, which consists of: $p(A=0)$ is the probability of *flat* transactions, $p(A=1)$ is the probability of *active* transactions, $p(D=1|A=1)$ is the conditional probability that *active* transactions move the price up, $p(D=-1|A=1)$ is the conditional probability that *active* transactions move the price down, S_U is the expected up size, and S_D is the expected *down* size.

Table 6 reports the parameter estimates of the Asymmetric Autoregressive Conditional Duration with Size (AACDS) model. Figure 3 displays the expected durations of the transaction prices, displaying both the expected adjusted flat durations (ψ_F^*) and the expected adjusted active durations (ψ_A^*). The smallest expected adjusted flat durations are 0.788 seconds for Intel and are 0.774 seconds for Microsoft. The same two securities also have the largest expected adjusted active durations, which are 8.387 seconds for Intel and are 7.322 seconds for Microsoft. In contrast, the expected adjusted duration for both directions are very similar for all securities. For example, the largest expected duration difference of 0.973 seconds is for Microsoft, which has an expected adjusted up duration of 15.146 seconds compared to an expected adjusted down duration of 14.173. Note that all of the intensities are the inverse of their associated expected adjusted durations. For example, Apple has the highest intensity for all transactions of $\lambda = 1.495$, which is the inverse of the expected adjusted duration for all transactions of $\psi^* = 1/\lambda = 0.669$. One again, the size variables are common to both asymmetric models and will be discussed later.

Figure 3: Expected Durations in Seconds



Notes: Figure 3 displays the expected durations of the transaction prices for the 21st of June 2012 for the five securities, namely, Apple, Amazon, Google, Intel, and Microsoft.

Table 6: Asymmetric Autoregressive Conditional Duration with Size (AACDS) model

	Apple	Amazon	Google	Intel	Microsoft
ψ^*	0.669	2.049	2.004	0.720	0.700
ψ_F^*	1.362	3.976	4.156	0.788	0.774
ψ_A^*	1.314	4.229	3.870	8.387	7.322
ψ_U^*	2.615	8.011	7.871	16.750	15.146
ψ_D^*	2.639	8.959	7.612	16.798	14.173
λ	1.495	0.488	0.499	1.388	1.428
λ_F	0.734	0.252	0.241	1.269	1.291
λ_A	0.761	0.237	0.258	0.119	0.137
λ_U	0.382	0.125	0.127	0.060	0.066
λ_D	0.379	0.112	0.131	0.060	0.071
S_U	6.537	6.045	10.747	1.395	1.548
S_D	6.780	7.013	11.308	1.515	1.548

Notes: Table 6 reports the parameter estimates for the Asymmetric Autoregressive Conditional Duration with Size (AACDS) model, which consists of: ψ^* is the expected *adjusted* duration, ψ_F^* is the expected *adjusted flat* duration, ψ_F^* is the expected *adjusted active* duration, ψ_A^* is the expected *adjusted up* duration, ψ_U^* is the expected duration, ψ_D^* is the expected *adjusted down* duration, λ is the intensity, λ_F is the *flat* (or *inactive*) intensity, λ_A is the total number of *active* intensity, λ_U is the *up* intensity, λ_D is the *down* intensity, S_U is the expected up size, and S_D is the expected *down* size.

The asymmetric models are equivalent and measure different aspects of the same asymmetric nature of high-frequency transaction data. Each model's parameter estimates can be used to estimate the other model's parameters exactly. For example, the expected adjusted flat duration for the AACDS model is 0.788 seconds for Intel and can be calculated from the parameter estimates of the ADS model by:

$$\psi_F^* = \frac{T}{N}\frac{1}{p(A=0)} = \frac{0.720}{0.914} = 0.788 \qquad (36)$$

where ψ_F^* is the expected adjusted *flat* duration, ψ^* is the expected adjusted duration for all transaction prices, and $p(A = 0)$ is the probability that transactions are flat. Similarly, the probability that transactions are active for the ADS model is 0.086 for Intel and can be calculated from the parameter estimates of the AACDS model by:

$$p(A = 1) = \frac{\psi^*}{\psi_A^*} = \frac{0.720}{8.387} = 0.086 \qquad (37)$$

where $p(A = 1)$ is the probability that transactions are active, ψ^* is the expected adjusted duration for all transaction prices, and ψ_A^* is the expected adjusted *active* duration.

Table 7: Common parameter estimates of the two asymmetric models

	Apple	Amazon	Google	Intel	Microsoft
w_F	0.491	0.516	0.482	0.914	0.904
w_U	0.256	0.256	0.255	0.043	0.046
w_D	0.253	0.229	0.263	0.043	0.049
S_U	6.537	6.045	10.747	1.395	1.548
S_D	6.780	7.013	11.308	1.515	1.548
$\boldsymbol{E(\Delta Z)}$	**-0.046**	**-0.058**	**-0.241**	**-0.005**	**-0.005**

Notes: Table 7 reports the common parameter estimates of the two asymmetric models consisting of: w_F is the *flat* weight, w_U is the *up* weight, w_D is the *down* weight, S_U is the expected *up size*, S_D is the expected *down size*, and $E(\Delta Z)$ is the expected change in the scaled price.

Table 7 reports the common parameter estimates of both asymmetric models. The expected values for both size variables are larger than one tick size for all securities, which justifies the inclusion of a size variable in the three-state Asymmetric Autoregressive Conditional Duration (AACD) model. Google has the highest expected tick sizes of 10.747 for up moves and 11.308 for down moves. In contrast, Intel has the lowest expected tick sizes of 1.395 for up moves and 1.515 for down moves. In addition, Amazon has the largest difference of 0.968 between the up size variable and the down size variable.

The expected values of $E(\Delta Z)$ for each security is negative, where the values are -0.046 for Apple, -0.058 for Amazon, -0.241 for Google, -0.005 for Intel, and -0.005 for Microsoft. Google has the largest expected value which can be seen by using Equation (34):

$$\begin{aligned} E(\Delta Z) &= w_U E(S_U) + w_D E(S_D) \\ &= 0.255 \times 10.747 - 0.263 \times 11.308 \\ &= -0.241 \end{aligned} \tag{38}$$

where $E(\Delta Z)$ is the expected change in the scaled price of the security, $E(S_F)$ is the expected *flat size*, $E(S_U)$ is the expected *up size*, and $E(S_D)$ is the expected *down size*.

Conclusion

This paper compared two asymmetric models of high-frequency transaction data in financial markets, namely, the Activity Direction Size (ADS) model and the three-state Asymmetric Autoregressive Conditional Duration with Size (AACDS) model. It was shown that both asymmetric models are equivalent and measure different aspects of the same asymmetric nature of high-frequency transaction data. The size variables plays an integral part of both asymmetric models, as the magnitude of price changes occur in multiples of the underlying tick size. Thus, the inclusion of two size variables in the AACD model extends it to model durations and price changes jointly: creating a more general model. The implication of this paper is that researchers can compare the parameter estimates of one model with the parameter estimates of the other model, especially when more sophisticated dynamic models are used: one model provides a yardstick for the other.

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THE MARKET VALUE OF DECENTRALISATION

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Abstract

A prominent motivation for the use of cryptocurrencies as a medium of exchange is that they do not require a central trusted authority. However, when exchanging one cryptocurrency for another, there are two classes of exchange. First is the centralised exchange, which requires trust in the exchange operator. Second, there are decentralised exchanges where participants can exchange cryptocurrencies using a protocol. This analysis uses the failure of the centralised FTX exchange to estimate the change in value the market assigns to decentralised versus centralised exchanges. We find evidence consistent with market participants assigning a significant value to decentralisation.

JEL Codes: G14; G23

Keywords: Decentralised Finance; Event Study

1. Introduction

The FTX exchange was founded in 2019 and grew rapidly to over one million users by 2021. FTX was a centralised exchange, meaning users created an account and deposited money with FTX, and trading took place on order books on FTX servers. In early November 2022, the FTX exchange suspended trading and filed for Chapter 11 bankruptcy. The proximate cause of the bankruptcy was the rapid withdrawals of money by customers which could not be met by FTX[1]. The withdrawals were fueled by speculation that FTX had fraudulently handled customer funds.

Specifically, the alleged fraud by FTX was to use customer assets to trade and as collateral for the FTX exchange. This particular type of fraud, however, could not occur when using decentralised exchanges such as Uniswap. The reason being, on decentralised exchanges, the assets are exchanged directly between the buyer and seller using a protocol as the transfer mechanism. In such a fashion, the transfer of assets does not require trust in any participant. It does require trust in the protocol; however, the protocols used are publicly available and can be audited by knowledgeable participants.

The goal of this analysis is to use the collapse of the FTX exchange to determine if market participants assign a significant value to decentralisation. If not, the tokens of decentralised and centralised

1 Wilson, Tom; Berwick, Angus (8 November 2022). "Crypto exchange FTX saw $6 bln in withdrawals in 72 hours". Reuters. Retrieved 18 November 2022. https://www.reuters.com/business/finance/crypto-exchange-ftx-saw-6-bln-withdrawals-72-hours-ceo-message-staff-2022-11-08/

exchanges should react similarly to the FTX collapse. However, if participants meaningfully value decentralisation, then the tokens of decentralised exchanges should outperform the tokens of centralised exchanges. The market capitalisation of decentralised exchanges should increase relative to centralised exchanges. Thus, in this analysis, we use an event study to test for significantly different abnormal returns during windows around the collapse of FTX.

In this analysis, we use the value of tokens issued by various centralised and decentralised exchanges. These tokens represent a vote in the governance of the exchange. Tokens may not presently receive fees from trading on the exchange; however, since they are governance tokens, they may enact fees in the future. For example, see the discussion[2] of turning off fees (known as the "fee switch") on the governance board of the Uniswap decentralised exchange.

Decentralised finance (also known as DeFi) is presently a focus of US regulatory bodies and researchers on market regulation. Zetzsche, Arner, and Buckley 2020 discuss DeFi and how regulatory oversight and risk control are important to realise the benefits of DeFi. DeFi and its implications are a prominent topic of interest for regulators. The US Treasury released a report in April 2023 (Treasury 2023) which highlighted the effects of DeFi on illicit financial transactions. Much of the regulatory scrutiny is on organisations enabling DeFi protocols, which includes organisations which offer DeFi tokens.

Recent research on the FTX collapse has focused on the contagion effect across markets. Yousaf and Goodell 2023 find evidence for reputational contagion during the collapse of the FTX exchange. Yousaf and Goodell 2023 find little evidence of contagion from the crypto to other asset markets during the collapse of FTX. Lastly, Jalan and Matkovskyy 2023 investigated the effect of the FTX collapse on systemic risk and found that it had little effect.

Tables 1 and 2 contain lists of the Centralised and Decentralised tokens in this analysis, as well as each token's ticker. Note, Apollo had a CEX until January 16th 2023, by which time all assets should be transferred to the DEX.

Table 1: Centralised Exchanges

Exchange	Token
FTX	FTT
Binance	BNB
iFinex	LEO
Cronos	CRO

Table 2: Decentralised Exchanges

Exchange	Token
Uniswap	UNI
PancakeSwap	CAKE
Apollo DEX	APX
1inch	1INCH

Previous analyses of cryptocurrencies focus on their potential function as a safe-haven asset (Mariana, Ekaputra, and Husodo 2021). Others have specifically investigated bubbles in DeFi assets (Maouchi, Charfeddine, and El Montasser, 2022, Geuder, Kinateder, and Wagner, 2019) and herding behaviour (Bashir, Kumar, and Shiljas, 2021). Additionally, there is a substantial amount of research on the macroeconomic factors which affect the returns on cryptocurrencies (Nakagawa and Sakemoto 2021, Bianchi 2020, Wang and Chong 2021, Jiang, Rodríguez Jr, and Zhang 2023) and how returns are affected by major events (Tang and Liu 2022).

[2] https://gov.uniswap.org/t/fee-switch-pilot-update-vote/19514

2. Data and Methods

Daily price data were gathered via the CoinMarketCap website and the Coinbase Application Programming Interface. The event date is November 9th, 2022, and the event window ranges from 10 days before the event to 10 days after (denoted CAR(-10, 10)). Our estimation window is six months prior to the start of the event window.

Our sample thus ranges from May 5th, 2022, through November 19th, 2022, for a total of 178 days. Note, since crypto assets trade continuously, daily prices are seven days per week.

Table 3: DEX Full Period Return Summary Statistics

	CAKE	UNI	APX	INCH
count	332.0000	332.0000	332.0000	332.0000
mean	-0.0022	-0.0018	-0.0023	-0.0036
std	0.0486	0.0573	0.0588	0.0477
min	-0.2710	-0.1974	-0.2046	-0.2150
25%	-0.0271	-0.0347	-0.0236	-0.0308
50%	0.0000	-0.0005	-0.0003	-0.0029
75%	0.0239	0.0296	0.0142	0.0248
max	0.1971	0.2142	0.5490	0.1822

Tables 3 through 8 provide return summary statistics over the full sample, as well as over the estimation and event windows. Token returns exhibit substantial volatility, with daily return standard deviations typically around 5% (and somewhat higher during the event window). Further, maximum token returns in absolute value are often over 15%, consistent with kurtosis in the return distributions.

Table 4: DEX Estimation Period Return Summary Statistics

	CAKE	UNI	APX	INCH
count	168.0000	168.0000	168.0000	168.0000
mean	0.0012	0.0035	-0.0026	-0.0015
std	0.0386	0.0578	0.0323	0.0447
min	-0.1649	-0.1295	-0.1486	-0.1106
25%	-0.0210	-0.0285	-0.0127	-0.0300
50%	0.0044	0.0021	-0.0012	-0.0032
75%	0.0222	0.0291	0.0090	0.0265
max	0.1273	0.2142	0.1090	0.1822

Table 5: DEX Event Period Return Summary Statistics

	CAKE	UNI	APX	INCH
count	21.0000	21.0000	21.0000	21.0000
mean	-0.0078	-0.0066	0.0059	-0.0060
std	0.0528	0.0782	0.0888	0.0463
min	-0.1608	-0.1914	-0.1707	-0.1244
25%	-0.0228	-0.0385	-0.0072	-0.0168
50%	-0.0083	-0.0056	0.0045	-0.0077
75%	0.0042	0.0380	0.0107	0.0242
max	0.1339	0.1755	0.3090	0.0779

Table 6: CEX Full Period Return Summary Statistics

	BNB	CRO	LEO	FTT
count	332.0000	332.0000	332.0000	332.0000
mean	-0.0010	-0.0054	0.0009	-0.0060
std	0.0388	0.0494	0.0460	0.0766
min	-0.1857	-0.2087	-0.1344	-0.7507
25%	-0.0200	-0.0262	-0.0132	-0.0236
50%	-0.0015	-0.0006	0.0000	0.0004
75%	0.0198	0.0212	0.0147	0.0234
max	0.1395	0.1806	0.5560	0.5304

Table 7: CEX Estimation Period Return Summary Statistics

	BNB	CRO	LEO	FTT
count	168.0000	168.0000	168.0000	168.0000
mean	0.0007	-0.0023	-0.0003	-0.0006
std	0.0331	0.0409	0.0283	0.0365
min	-0.1307	-0.1767	-0.1344	-0.1296
25%	-0.0128	-0.0189	-0.0104	-0.0180
50%	-0.0006	0.0000	0.0000	0.0006
75%	0.0158	0.0204	0.0147	0.0228
max	0.0907	0.1244	0.1366	0.0964

Table 8: CEX Event Period Return Summary Statistics

	BNB	CRO	LEO	FTT
count	21.0000	21.0000	21.0000	21.0000
mean	-0.0035	-0.0168	-0.0023	-0.0805
std	0.0588	0.0926	0.0318	0.2584
min	-0.1857	-0.2087	-0.0874	-0.7507
25%	-0.0204	-0.0413	-0.0096	-0.1196
50%	-0.0070	-0.0079	0.0022	-0.0325
75%	0.0224	0.0367	0.0155	-0.0058
max	0.1395	0.1806	0.0446	0.5304

We use an event-study methodology to calculate cumulative abnormal returns for both decentralised and decentralised exchange tokens around the collapse of FTX. We then group the returns into CEX and DEX portfolios, and test for significantly different cumulative abnormal returns between the portfolios.

We use a market model to estimate expected returns in the abnormal return calculation. Specifically, we have:

$$AR_{i,t} = r_{i,t} - E(r_{i,t}) = r_{i,t} - (\alpha_i + \beta_i r_{m,t})$$

where $AR_{i,t}$ and $r_{i,t}$ denote the abnormal return, and log return, on asset *i* at time *t* respectively. Abnormal returns are calculated for each day over the event window ranging from 10/30/2022 to

11/19/2022. Cumulative abnormal returns are the cumulative sum of abnormal returns over the event window.

The term $r_{m,t}$ denotes the return on the market at time t. We define the market as a market-weighted index of Bitcoin and Ethereum prices. Attempting to use equity market indexes (such as the CRSP value-weighted index or the S&P 500) is problematic for several reasons. Since equity markets are closed over the weekend, though crypto markets are not, we would lose observations matching equity and crypto returns. Also, the weekended effect may be different between markets. Additionally, there is a higher correlation between the token returns and Bitcoin and Ethereum returns relative to equity market returns. The α_i and β_i terms are coefficients from the regression $r_{i,t} = \alpha_i + \beta_i r_{m,t} + e_t$ estimated over the estimation period ranging from 5/15/2022 to 10/29/2022.

We then test for significantly different group cumulative abnormal returns with the following t-test:

$$t = \frac{CAR_{DEX} - CAR_{CEX}}{\sqrt{\frac{\hat{\sigma}^2_{DEX}+\hat{\sigma}^2_{CEX}}{2}}\sqrt{\frac{2}{n}}}$$

where *CAR* denotes the cumulative abnormal return over the event window, $\hat{\sigma}^2$ denotes the variance of abnormal returns, and *n* is the length of the event window.

Note results of any event study are going to be affected by the choice of event window. To wide a window risks including the effect of unrelated events, and too narrow a window may omit leading and lagged effects of the event. We use a standard window length (10 days before and after the event date, CAR(-10, 10)) commonly employed in event studies in equity markets. We also check for robustness with a CAR(-5, 5) window length.

4. Results and Conclusion

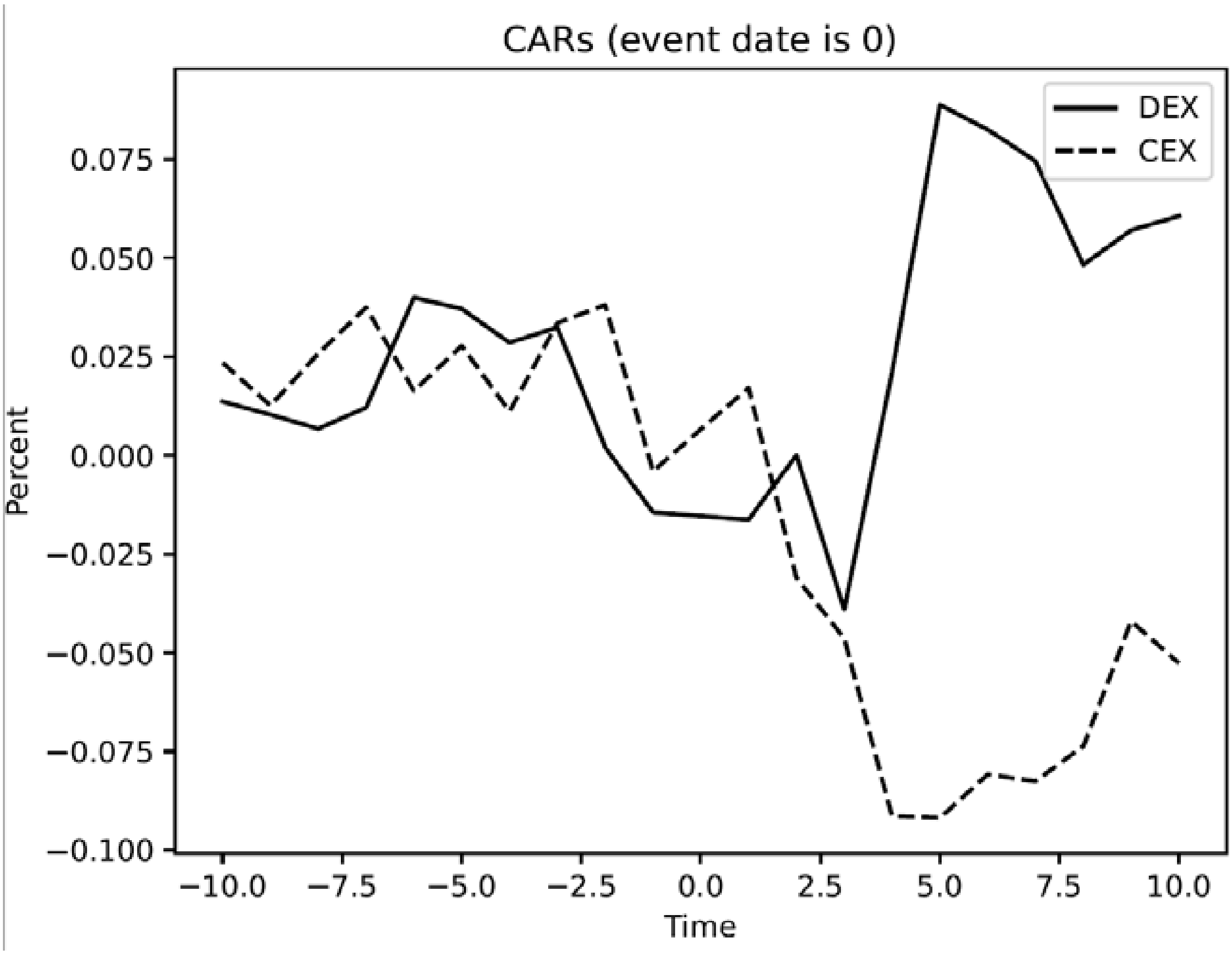
The mean DEX CAR(-10, 10) was 6.06%, and the mean CEX (excluding FTT) CAR(-10, 10) was -5.62%. A t-test on the difference of the CARs yields a t-statistic of 3.59, and so we conclude DEXs performed significantly better than CEXs around the collapse of the FTX exchange. This is evidence that market participants assign a significant value to decentralisation. Further, the relative value of decentralisation versus centralisation increased during the FTX collapse.

Using the more narrow CAR(-5, 5) window we find mean DEX CAR was 4.75%, and the mean CEX (excluding FTT) CAR(-5, 5) was -11.35%. A t-test on the difference of the CARs yields a t-statistic of 3.27. This evidence further supports the conclusion that decentralisation was valued around the collapse of the FTX exchange.

Previous research on the FTX collapse has found that it negatively affected crypto assets (Yousaf and Goodell 2023), however it generally did not affect other asset classes (Yousaf, Riaz, and Goodell 2023, Jalan and Matkovskyy 2023). Our analysis has found evidence that the FTX collapse increased the relative value of decentralisation compared to traditional centralised exchange.

Decentralised exchanges are recent financial innovations, and this analysis supports their value to market participants relative to centralised exchanges. These decentralised exchanges are also increasingly under regulatory scrutiny. This analysis is thus informative for regulators considering whether to attempt to regulate the core innovation of decentralised exchange.

Figure 1:



Mean Cumulative Abnormal returns for DEX and CEX tokens around the failure of the FTX exchange (CEX CARs do not include the FTT token).

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DOES LEVERAGE PAY OFF? THE CASE OF EQUITY-LEVERAGED MUTUAL FUNDS

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Abstract

In this study, we examine the risk-adjusted performance of a sample of U.S.-based enhanced index mutual funds that use leverage to generate return multiples of their benchmark. We study equity-leverage funds that follow four major market indices: the Dow Jones Industrial Average, the NASDAQ-100, the Russell 2000, and the Standard and Poor's 500. We consider two model specifications to measure risk-adjusted performance and different market conditions. The evidence shows that these funds fail to outperform. This is particularly true during favourable market conditions.

JEL Codes: G10; G11

Keywords: Mutual funds; enhanced index strategy; leverage; risk-adjusted performance

1. Introduction

Although financial innovations like exchange-traded funds (ETFs), cryptocurrencies, and zero-commission trading have revolutionized investors' portfolios, open-end mutual funds are still an important investment vehicle for U.S. investors. In fact, the U.S. mutual fund industry remains the largest in the world, with $23.9 trillion in total assets at the end of 2020, and 89% of that is in the hands of retail investors[1]. It is safe to say that, despite a very different U.S. investment landscape, mutual funds are still one of the go-to assets for most individual investors.

Generally, mutual funds offer investors access to a professionally managed, low-cost, diversified portfolio. Furthermore, as markets evolve, so do managers' tactics in their quest to generate value for funds' investors. A case in point is leverage. Although a tool commonly used by hedge funds, more than 70% of all hedge funds use it (Liang and Qiu, 2019), slowly but surely, open-end mutual funds are beginning to rely on leverage in their quest to generate excess returns. However, given the long list of restrictions they face, mutual funds continue to use many other trading tactics to compensate for the limited amount of leverage (no more than 33.33% of total assets) they can use[2]. This study examines the risk-adjusted performance of a sample of enhanced index mutual funds (EIFs). EIFs use the return of a specified index as a reference point and attempt to provide a return higher than that of this index.

[1] Investment Company Institute 2021 Fact Book.

[2] 2011 Commission Concept Release: Use of Derivatives by Investment Companies under the Investment Company Act of 1940, Security and Exchange Commission.

Moreover, they are commonly described as a hybrid between actively and passively managed funds. Our sample of equity EIFs uses leverage to increase the fund's exposure to its benchmark to generate a multiple of the return generated by the index. A strategy that could pay off during good market conditions but be disastrous when markets fall. We examine equity-leverage EIFs that follow four major market U.S. indices: the Dow Jones Industrial Average (Dow), the NASDAQ-100, the Russell 2000 and the Standard and Poor's 500.

2. Literature Review

Our study contributes to the mature but still active literature on mutual funds risk-adjusted performance. In general, the academic literature indicates mutual fund managers do not have skill (Elton, Gruber, Das, and Hlvaka 1993; Gruber, 1996; Fama and French, 2010), but some studies suggest unique metrics and fresh datasets that can identify managers who outperform (Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009; Berk and Van Binsbergen, 2015).

We are not the first to examine the performance of EIFs. Riepe & Werner (1998) studied eight enhanced index funds (EIFs) and concluded that most funds did not provide a superior return compared to the S&P500 index. An examination of the EIFs in the Chinese market also showed that these funds performed worse than their benchmark (Weng & Wang, 2017). Chen et al. (2012) use the bootstrap technique to analyze the performance of EIFs over the 1996 to 2007 period and report positive and significant alphas.

In addition to comparing the performance of EIFs with that of their respective benchmarks, some studies compare EIFs against passive index mutual funds. Tower and Yang (2008) report that the enhanced-index strategy outperformed the passive index strategy over the eight-year period 1999-2006. Another comparison between enhanced and passive index strategies documents that, during index revision periods, enhanced index funds exhibit higher returns and lower trading costs (Frino et al., 2005). Chang and Krueger (2010) compare operating characteristics and performance measures with data up to 2009 and find that EIFs generally exhibit higher expense ratios, annual turnover rates, and lower risk-adjusted returns. Ahmed and Nanda (2005) compare the performance of EIFs and quantitative equity funds. They present evidence of outperformance by quantitatively managed growth funds.

EIFs have the dual objective of outperforming a benchmark index while maintaining a low tracking error. The portfolio selection strategy to enhance the index varies between EIFs. Roman et al. (2013) evaluate the Second order Stochastic Dominance (SSD) model of portfolio choice for data drawn from the following three indexes: FTSE 100, S&P500 and Nikkei 225. They conclude that SSD-based models consistently outperform these indexes and the passive index strategies. Clark et al. (2019) propose a new strategy called the utility-enhanced tracking technique that generates consistently higher after-expenses returns. Wu et al., 2007 propose a strategy based on goal programming that does not require a fund manager to buy and sell stocks actively to improve returns. Empirical results show that this strategy lowered transaction costs and produced sustainable risk-controlled enhanced returns.

Using leverage by mutual funds is still a relatively new research topic with only a few studies. Warburton and Simkovic (2019) compare mutual funds that use leverage (in the form of bank loans) versus their non-borrowing peers and find that borrowers underperform and incur greater risk. Finally, Molestina-Vivar et al. (2020) study the link between mutual fund leverage and investor flows and report greater outflows during stressed periods and after negative returns. To the best of our knowledge, no academic study examines the risk-adjusted performance of EIFs that use leverage to attempt to outperform their benchmark.

3. Data and Methods

We examine the risk-adjusted performance of U.S.-based enhanced index funds that use leverage to increase their exposure to a multiple of its benchmark to magnify the index return. The samples of funds come from the Chicago Research in Security Prices Mutual Fund Database (CRSP) and include all open-end mutual funds classified by Lipper as equity-leverage funds. We select funds with major indices as benchmarks. These include the Dow Jones Industrial Average (Dow), the NASDAQ-100, the Russell 2000 and the Standard and Poor's 500 (S&P 500). For funds with multiple classes, we include the class with the longest history in the sample. These filters yield a sample of 19 unique funds listed in Table 1 and distributed as Dow (5 funds), NASDAQ (8), Russell 2000 (2) and S&P 500 (4).

Table 1: List of Fund Names

	Family Name	Fund Name	Index Name
1	Rydex Series Funds	Russell 2000 1.5x Strategy Fund	Russell
2	Rydex Dynamic Funds	Russell 2000 2x Strategy Fund	Russell
3	Direxion Funds	Direxion Monthly S&P 500 Bull 2x Fund	SP500
4	Rydex Dynamic Funds	S&P 500 2x Strategy Fund	SP500
5	Advisors' Inner Circle Fund	Toews S&P 500 Hedged Index Fund	SP500
6	Rydex Variable Trust	S&P 500 2x Strategy Fund	SP500
7	Rydex Dynamic Funds	Dow 2x Strategy Fund	Dow
8	Rydex Variable Trust	Dow 2x Strategy Fund	Dow
9	ProFunds	UltraDow 30 ProFund	Dow
10	Potomac Funds	Potomac Dow 30 Plus Fund	Dow
11	Rydex Dynamic Funds	Dow 2x Strategy Fund	Dow
12	Direxion Funds	Direxion Monthly NASDAQ-100 Bull 2x Fund	Nasdaq
13	ProFunds	UltraNASDAQ-100 ProFund	Nasdaq
14	Rydex Dynamic Funds	NASDAQ-100 2x Strategy Fund	Nasdaq
15	ProFunds	ProFund VP UltraNASDAQ-100	Nasdaq
16	Rydex Variable Trust	NASDAQ-100 2x Strategy Fund	Nasdaq
17	Rydex Series Funds	Monthly Rebalance NASDAQ-100 2x Strategy Fund	Nasdaq
18	Direxion Funds	Direxion Monthly NASDAQ-100 Bull 1.25X Fund	Nasdaq
19	Advisors' Inner Circle Fund	Toews Nasdaq-100 Hedged Index Fund	Nasdaq

Since these funds are designed to magnify index returns daily, we use daily data for all the analyses. Daily fund returns are from CRSP, Bloomberg is used for the set of market indices, and the daily Fama-French factors are from the Kenneth R. French Data Library. The time period of the study runs from 2001 to 2022. We use several performance metrics, starting with excess returns and the Sharpe ratio. We then measure how frequently these funds meet their performance mandate. Funds in the sample seek to generate 1.5 to 2 times the daily return of their benchmark. To be conservative in measuring the number of times, the funds meet their mandate, we assume a mandate of 2X. This way, we do not exaggerate the good performance of any fund.

On the contrary, our empirical results have a downward bias, as we impose a higher standard on some of the funds in the sample. Given the investment objective of this sample of funds, that is, to leverage up to generate a higher performance than that of the index they follow, it is important to examine their performance in a wide range of market conditions. To that end, we consider weak (Bear) versus strong (Bull) market conditions. Bear and Bull markets are based on data provided by www.thedowtheory.com. We also consider market condition partitions based on NBER recession data obtained from https://fred.stlouisfed.org and index return percentiles.

4. Empirical Results

Table 2: Excess Return Statistics and Sharpe Ratio

Portfolio	Market Condition	Number of Obs.	Index Return Mean	Excess Return Mean		Excess Return Std Dev	Excess Return Median	Portfolio Sharpe Ratio	Index Sharpe Ratio
Panel A: by Market Condition (Bull vs. Bear)									
Dow	Bear	1068	-0.0014	-0.0012	**	0.0153	-0.0005	-0.0788	-0.0779
Dow	Bull	4467	0.0007	0.0006	***	0.0090	0.0007	0.0685	0.0652
Nasdaq	Bear	1068	-0.0020	-0.0019	**	0.0276	-0.0002	-0.0755	-0.0729
Nasdaq	Bull	4467	0.0010	0.0008	***	0.0107	0.0007	0.0760	0.0776
Russell	Bear	626	-0.0023	-0.0017	**	0.0199	-0.0010	-0.0886	-0.0898
Russell	Bull	4095	0.0008	0.0005	***	0.0098	0.0008	0.0546	0.0536
SP500	Bear	922	-0.0018	-0.0012		0.0225	-0.0003	-0.0767	-0.0907
SP500	Bull	4467	0.0007	0.0006	***	0.0099	0.0004	0.0681	0.0689
Panel B: by Market Condition (NBER Recession)									
Portfolio	**Market Condition**	**Number of Obs.**	**Index Return Mean**	**Excess Return Mean**		**Excess Return Std Dev**	**Excess Return Median**	**Portfolio Sharpe Ratio**	**Index Sharpe Ratio**
Dow	Recession	586	-0.0006	-0.0005		0.0207	-0.0002	-0.0256	-0.0274
Dow	No Recession	4949	0.0004	0.0004	***	0.0086	0.0005	0.0390	0.0337
Nasdaq	Recession	586	0.0000	-0.0008		0.0328	-0.0001	-0.0158	-0.0037
Nasdaq	No Recession	4949	0.0005	0.0004	**	0.0119	0.0004	0.0313	0.0293
Russell	Recession	420	-0.0007	-0.0005		0.0246	0.0003	-0.0220	-0.0239
Russell	No Recession	4301	0.0005	0.0003	**	0.0095	0.0006	0.0325	0.0321
SP500	Recession	502	-0.0008	-0.0006		0.0292	0.0001	-0.0255	-0.0314
SP500	No Recession	4887	0.0004	0.0004	***	0.0099	0.0003	0.0410	0.0348
Panel C: by Market Return Percentile (Bottom25%, Top25%)									
Portfolio	**Market Condition**	**Number of Obs.**	**Index Return Mean**	**Excess Return Mean**		**Excess Return Std Dev**	**Excess Return Median**	**Portfolio Sharpe Ratio**	**Index Sharpe Ratio**
Dow	Bottom	1385	-0.0127	-0.0108	***	0.0100	-0.0083	-1.1540	-1.1897
Dow	Top	1383	0.0127	0.0109	***	0.0094	0.0088	1.2245	1.2379
Nasdaq	Bottom	1385	-0.0173	-0.0144	***	0.0174	-0.0106	-1.1220	-1.2404
Nasdaq	Top	1383	0.0170	0.0138	***	0.0141	0.0110	1.1334	1.1623
Russell	Bottom	1116	-0.0175	-0.0128	***	0.0107	-0.0106	-1.2360	-1.2608
Russell	Top	1153	0.0169	0.0124	***	0.0095	0.0103	1.3427	1.3558
SP500	Bottom	1332	-0.0139	-0.0103	***	0.0153	-0.0085	-1.0128	-1.2903
SP500	Top	1343	0.0137	0.0104	***	0.0146	0.0095	1.0868	1.3528

Note: *All the results are based on daily returns. ***, **, * corresponds to 1%, 5%, and 10% statistical significance.*

We employ daily returns to examine the risk-adjusted performance of a sample of 19 EIFs that use as benchmark one of the four U.S. major stock indices: Dow Jones Industrial Average (Dow), the NASDAQ-100, the Russell 2000 and the Standard and Poor's 500 (S&P 500). We start by computing an equally weighted portfolio of all the funds that follow each particular index. Table 2 shows the analyses based on excess returns, that is, the difference between the return of each portfolio of funds and that of their index benchmark. This first set of results considers a variety of market conditions. Panel A presents the results for Bull versus Bear market conditions. We find significant excess returns that are positive during Bull markets and negative during Bear markets. All mean excess returns significantly differ from zero at 1 or 5 percent levels. The only insignificant excess return is for the SP 500 portfolio during Bear market conditions. The results for the Sharpe Ratio in Panel A are similar to that of the excess returns. The Sharpe ratio is positive during Bull market conditions and negative during Bear market conditions. This behaviour of the Sharpe is consistent through the other two panels of the table where the measure of market conditions is the NBER recessions marker (Panel B) and top versus bottom market return (Panel C).

In Panel B of Table 2, we show the analysis of excess returns during periods when the economy was in a recession or not. We find positive and statistically significant excess returns during non-recession periods. During recessions, excess returns are all insignificant. Again, the significance level ranges between 1 and 5 percent. Finally, Panel C considers the top and bottom market return percentiles. Results are similar to those in Panel A; however, all excess returns are higher in magnitude and significant at the 1 percent level. Again, excess returns are significantly positive when the market reaches top performance and negative during periods of worse performance. Regardless of the index, all funds perform significantly better during good market conditions than during challenging times. This is particularly true for partitions based on the actual market return. It is worth mentioning that the results in Table 2 show that in terms of magnitude, excess returns during bear markets are negative and 2 to 4 times larger than the positive excess returns in bull markets. Thus, the additional leverage these funds employ manifests more during difficult bad times than during good times.

As a second step in gauging the performance of this sample of equity-leverage enhanced index funds, we measure the number of trading days each portfolio meets its mandate in terms of amplifying its benchmark daily return. Results are presented in Table 3. Panel A of Table 3 shows this frequency based on a mandate of 2X the benchmark daily return. Considering the full sample, funds meet their mandate 44 percent of the time. The most effective group is the Russell portfolio (47%), followed by the SP 500 (46%), Nasdaq (43%) and finally, the Dow (42%). Panel B of Table 3 presents the results of the same analysis but considering Bull versus Bear market conditions. Comparing the results presented in both panels, we can see that have the funds meet their mandate more frequently during Bear markets conditions than during Bull markets. The Dow portfolio is an example of this. The Dow funds meet their mandate 46 percent during Bear markets versus 41 percent during Bull markets. The same happens with the Russell portfolio (53% versus 46%). For both, the Nasdaq and the SP 500, funds meet their mandate more frequently during Bull markets.

We now turn to measuring funds' risk-adjusted performance. To that end, we rely on two model specifications: a daily single-factor alpha and the daily Fama-French five-factor model. Table 4 shows the results for the single factor, and again, we consider three measures of market conditions. Panel A presents the results for the Bull/Bear market partition. The only significant single-factor alpha is that of the Russell portfolio during Bull market conditions. This alpha is negative and significant. The Gibbons, Ross, and Shanken (1989) GRS test rejects the null hypothesis that the alphas of the portfolios are jointly zero, but only during Bull market conditions. Panel B shows the results based on whether the economy is facing a recession or not. These results are extremely similar to those in Panel A, and we reach the same conclusions. However, the results on Panel C are very different from those of Panel A and B. The partition here is based on the Top versus Bottom market index return. We find that all alphas, but one (Nasdaq during Top Market Return Percentile), are significant at the 1 percent level. For both the Dow and SP 500 portfolios, the single-factor alpha is positive for the bottom percentile and negative for the top percentile. For the Russell portfolio, the contrary is true. Alpha is positive for the top percentile and negative for the bottom. Regardless of the percentile, the GRS test rejects the null hypothesis that the alphas of the portfolios are jointly zero.

Table 3: Performance versus Funds' Mandate

Panel A: Frequency of Days with Return above Mandate by Portfolio			
Portfolio	**No**	**Yes**	**Total**
Dow	3,187	2,348	5,535
	58%	42%	100%
Nasdaq	3,152	2,383	5,535
	57%	43%	100%
Russell	2,522	2,199	4,721
	53%	47%	100%
SP500	2,900	2,489	5,389
	54%	46%	100%
Total	**11,761**	**9,419**	**21,180**
	56%	**44%**	**100%**

Panel B: Frequency of Days with Return above Mandate by Portfolio and Market Condition (Bull vs. Bear)			
	Market Condition = Bear		
Portfolio	**No**	**Yes**	**Total**
Dow	572	496	1,068
	54%	46%	100%
Nasdaq	577	491	1,068
	63%	38%	100%
Russell	295	331	626
	47%	53%	100%
SP500	588	334	922
	64%	36%	100%
Total	**2,032**	**1,652**	**3,684**
	55%	**45%**	**100%**
	Market Condition = Bull		
Portfolio	**No**	**Yes**	**Total**
Dow	2,615	1,852	4,467
	59%	41%	100%
Nasdaq	2,575	1,892	4,467
	58%	42%	100%
Russell	2,227	1,868	4,095
	54%	46%	100%
SP500	2,312	2,155	4,467
	52%	48%	100%
Total	**9,729**	**7,767**	**17,496**
	56%	**44%**	**100%**

Note: All the results are based on daily returns. The above mandate means that the portfolio return is greater than twice the index return.

Table 4: Single-factor Alpha

Portfolio	Market Condition	Number of Obs.	Alpha	t statistic	p-value
Panel A: Market Condition (Bull vs. Bear)					
Dow	Bear	1068	0.0000	0.1298	0.8967
Dow	Bull	4467	-0.0001	-1.1984	0.2308
Nasdaq	Bear	1068	-0.0002	-0.2853	0.7755
Nasdaq	Bull	4467	0.0001	0.9045	0.3658
Russell	Bear	626	-0.0001	-0.1428	0.8865
Russell	Bull	4095	-0.0003	-2.4469	0.0144
SP500	Bear	922	0.0002	0.2993	0.7648
SP500	Bull	4467	-0.0001	-1.2684	0.2047
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Bear	626	0.0000	0.0272	0.9986
GRS test	Bull	4095	-0.0001	2.9614	0.0187
Panel B: Market Condition (NBER Recession)					
Portfolio	**Market Condition**	**Number of Obs.**	**Alpha**	**t statistic**	**p-value**
Dow	Recession	586	-0.0002	-0.5413	0.5885
Dow	No Recession	4949	0.0000	0.4386	0.6610
Nasdaq	Recession	586	0.0002	0.1330	0.8942
Nasdaq	No Recession	4949	-0.0001	-0.5045	0.6139
Russell	Recession	420	0.0001	0.1497	0.8810
Russell	No Recession	4301	-0.0003	-2.0505	0.0404
SP500	Recession	502	0.0001	0.1271	0.8989
SP500	No Recession	4887	0.0000	0.3421	0.7323
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Recession	420	0.0001	0.2919	0.8832
GRS test	No Recession	4301	-0.0001	2.4296	0.0456
Panel C: Market Return Percentile (Bottom 25%, Top 25%)					
Portfolio	**Market Condition**	**Number of Obs.**	**Alpha**	**t statistic**	**p-value**
Dow	Bottom	1385	0.0018	5.3706	0.0000
Dow	Top	1383	-0.0019	-5.5100	0.0000
Nasdaq	Bottom	1385	-0.0041	-4.7446	0.0000
Nasdaq	Top	1383	-0.0002	-0.3094	0.7571
Russell	Bottom	1116	-0.0023	-4.4351	0.0000
Russell	Top	1153	0.0036	6.1644	0.0000
SP500	Bottom	1332	0.0038	7.5206	0.0000
SP500	Top	1343	-0.0028	-4.9426	0.0000
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Bottom	1116	-0.0002	35.8180	0.0000
GRS test	Top	1153	-0.0003	63.8000	0.0000

***Note**: All the results are based on daily returns.*

Table 5: Five-factor Alpha

Panel A: Market Condition (Bull vs. Bear)					
Portfolio	**Market Condition**	**Number of Obs.**	**Alpha**	**t statistic**	**p-value**
Dow	Bear	1068	-0.0004	-1.8476	0.0649
Dow	Bull	4467	-0.0002	-2.5975	0.0094
Nasdaq	Bear	1068	0.0005	0.7186	0.4725
Nasdaq	Bull	4467	0.0001	1.2113	0.2259
Russell	Bear	626	0.0002	1.5231	0.1282
Russell	Bull	4095	-0.0002	-5.4158	0.0000
SP500	Bear	922	-0.0002	-0.3689	0.7123
SP500	Bull	4467	-0.0001	-1.7568	0.0790
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Bear	626	0.0000	1.4566	0.2139
GRS test	Bull	4095	-0.0001	8.9578	0.0000
Panel B: Market Condition (NBER Recession)					
Portfolio	**Market Condition**	**Number of Obs.**	**Alpha**	**t statistic**	**p-value**
Dow	Recession	586	-0.0004	-1.2340	0.2177
Dow	No Recession	4949	-0.0001	-1.8847	0.0595
Nasdaq	Recession	586	0.0004	0.3987	0.6903
Nasdaq	No Recession	4949	0.0002	1.4250	0.1542
Russell	Recession	420	0.0000	0.1917	0.8480
Russell	No Recession	4301	-0.0001	-4.7308	0.0000
SP500	Recession	502	0.0000	-0.0999	0.9204
SP500	No Recession	4887	0.0000	-0.2163	0.8288
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Recession	420	0.0000	0.6235	0.6459
GRS test	No Recession	4301	-0.0001	7.1304	0.0000
Panel C: Market Return Percentile (Bottom 25%, Top 25%)					
Portfolio	**Market Condition**	**Number of Obs.**	**Alpha**	**t statistic**	**p-value**
Dow	Bottom	1385	0.0003	0.8985	0.3691
Dow	Top	1383	-0.0010	-3.6139	0.0003
Nasdaq	Bottom	1385	-0.0017	-2.1956	0.0283
Nasdaq	Top	1383	-0.0006	-0.9744	0.3300
Russell	Bottom	1116	0.0010	6.5355	0.0000
Russell	Top	1153	-0.0012	-8.0331	0.0000
SP500	Bottom	1332	0.0028	5.4809	0.0000
SP500	Top	1343	-0.0023	-4.2173	0.0000
		Number of Obs.	**Average Alpha**	**GRS statistic**	**GRS p-value**
GRS test	Bottom	1116	0.0004	17.2284	0.0000
GRS test	Top	1153	-0.0010	40.7956	0.0000

***Note**: All the results are based on daily returns.*

The last set of results are presented in Table 5. This table shows the results of alpha based on the Fama-French five-factor specification. In the Bull/Bear partition case, all significant alphas are negative. Regardless of market conditions, the alphas of the Nasdaq portfolio are not statistically significant. Also insignificant is the Russell alpha during Bear markets. The GRS test rejects the null hypothesis that the portfolios earn zero abnormal returns jointly during bull markets. The analysis that considers market conditions with NBER partitions in Panel B presents only two alphas (Dow and Russell) that are statistically significant, both negative and both during non-recession periods. Again, the GRS test rejects the null hypothesis that the portfolios jointly earn zero abnormal returns during no-recessions. Finally, Panel C shows only two insignificant alphas. The Dow portfolio attained a negative and significant alpha for the top percentile. This is also the case for the Russell and SP 500 portfolios. Two alphas are positive and significant for the bottom percentile (Russell and SP 500). In line with the results for the single-factor alpha, for both percentiles, the GRS test rejects the null hypothesis that the alphas of the portfolios are jointly zero. In sum, alphas are mostly negative. Based on the single-factor specification, there are only nine instances where a portfolio attained a significant alpha, six negative. Twelve alphas are significant when the five-factor model is employed; eleven are negative. Thus, regardless of market conditions, this sample of equity-leverage enhanced index funds fails to consistently beat their respective market benchmarks in the aggregate.

5. Conclusion

This study examines the risk-adjusted performance of a sample of equity-leverage mutual funds with enhanced index investment mandates. The sample includes funds that follow the Dow Jones Industrial Average, the NASDAQ-100, the Russell 2000 and the Standard and Poor's 500. We examine performance during a variety of market conditions. Our results show that this sample of equity-leverage funds generates significant excess returns, mostly positive during good market conditions and negative during adverse conditions. We also ask whether this sample of funds meets their mandate of generating x times the index's return. In that regard, the results show that funds meet their mandate on average during less than half of the total trading days included in the sample period.

Regarding risk-adjusted performance, we consider two model specifications, a single-factor and a Fama-French five-factor formulation. The evidence shows that these funds fail to outperform their market index in the aggregate. This is particularly true during periods of favourable market conditions. An important limitation of the study is the sample size. Future studies should aim to examine a larger sample.

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PRODUCTIVITY UNCERTAINTY AND STOCK PRICE CRASH RISK

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Abstract

This study examines the impact of productivity uncertainty on stock price crash risk. Empirical results show that higher productivity uncertainty contributes to higher stock price crash risk. This effect holds firmly after addressing potential endogeneity and the performing of robustness tests. Moreover, the positive impact of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition and less independent boards. The findings of this study are meaningful as they offer a risk-based explanation for stock price crash risk which is based on the presumption of investors' behaviours, and the examination of channel effect further supports this view.

JEL Codes: G30, G32

Keywords: **Productivity Uncertainty, Stock Price Crash Risk, Monitoring**

1. Introduction

The distribution of stock returns is often non-symmetric and displays negative skewness. It means that sizable negative stock returns are more frequently observed than large positive stock returns, a phenomenon referred to the concept of stock price crash risk (Harvey and Siddique, 2000; Chen et al., 2001; Conrad et al., 2013; Kim et al., 2014). The mainstream argument for the cause of stock price crash risk, as evidenced by Jin and Myers (2006), Hutton et al. (2009), and Kothari et al. (2009), is based on the notion that management has motivations to hoard negative news for prolonged periods of time. After the cumulation of negative news reaches the tipping point, the sudden release to the market leads the stock price to plummet. Guided by this argument, from different perspectives, various groups of subsequent studies have made efforts to explore factors that would potentially affect the stock price crash risk: financial reporting (e.g., Hutton et al., 2009; De Fond et al., 2015; Kim et al., 2016; Chen et al., 2017a); managerial incentives (e.g., Kim et al., 2011a; He, 2015; Park, 2017); capital market characteristics (e.g., Chen et al., 2001; Callen and Fang, 2015b; Chang et al., 2016); corporate governance (e.g., Xu et al., 2014; Andreou et al., 2016; Chen et al., 2017b); informal institutions (e.g., Callen and Fang, 2015a; Cao et al., 2016; Lee and Wang, 2017).

However, could companies' stock price crash risk be due to the nature of their fundamental business risk? This is an aspect that has received little attention by previous studies. For example, energy companies may have very risky field operations and are subject to the fluctuations of global energy price movements; technology companies may have niche markets and face fierce competition. If positive news and negative news are not symmetrically released or priced by the market, then stock returns of those firms may exhibit negative skewness, i.e., stock price crash risk. Cao et al. (2002) lay the groundwork for this risk-based explanation. Their study introduces the "information blockage effect". The effect indicates that an upward stock price trend is forged and maintained by informed investors through active trading. But less informed investors normally are wary and delay their market participation until the stock price plummets. In other words, bullish stock price movements are mainly pushed up by informed investors. However, bearish stock price movements are compounded by the selloffs of both informed and less informed investors. Hong & Stein (2003) laterally support the "information blockage effect" by proposing a model based on investors' opinions. Their model suggests that bearish investors normally don't participate in the market in time because of short-sales constraints so their negative sentiment is not revealed initially. However, when bullish investors exit the market, those originally bearish investors tend to become marginal buyers. Hence, the prior hidden negative information shows up and leads to the stock price crash. Moreover, the "information blockage effect" also echoes the so-called "volatility feedback effect". Proposed by prior studies such as French et al. (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), Wu (2001), and Carr and Wu (2017), the "volatility feedback effect" suggests that investors would re-adjust their assessment of stock volatility and increase required risk premiums when they observe stock price movements in large magnitudes. This investing behaviour tends to reinforce the impact of negative information but offset the effect of positive information, thus leading to the formation of negative skewness. Therefore, based on the two effects proposed by prior studies, it is plausible to envision that firms' business risk might be related to stock price crash risk.

A firm's business risk is largely captured by its productivity uncertainty, measured by the riskiness of cash flow per unit of asset (Zhao and Sing, 2016). Previous literature indicates that firms with higher productivity uncertainty, though proxied by different factors, exhibit greater financial constraints in various channels. Moshirian et al. (2017) and Harris and Roark (2019) document that firms with high productivity uncertainty exhibit low levels of capital investment. The values of prospective investment projects are determined by firms' discount rates. However, firms with high productivity uncertainty are considered risky so their discount rates are high because investors would demand high rates of return to compensate for bearing the risk. High discount rates effectively make many potential investment projects unprofitable and force those firms to forgo a large percentage of them. Sometimes those companies may have to invest in projects with negative NPVs and subsequently, firm values are decreased. Hirth and Uhrig-Homburg (2010) and Hirth and Viswanatha (2011) suggest that firms with high productivity uncertainty are associated with high financing costs and possible liquidity issues. When markets experience friction and shocks, this effect is largely magnified. Keefe and Yaghoubi (2016) echo these studies by showing that productivity uncertainty has a significant impact on capital structure, as firms with higher cash flow risk tend to use higher financial leverage and are subject to greater distress risk. In summary, although these prior studies are from different perspectives and yield different results of productivity uncertainty, they all support the argument that higher productivity uncertainty implies higher financial risk. Since financial risk is observed and priced by investors who are subject to the aforementioned "information blockage effect" and "volatility feedback effect", productivity uncertainty is hypothesized to be positively associated with stock price crash risk.

Using a comprehensive dataset from 2001 to 2021, this study finds that productivity uncertainty is significantly positively associated with stock price crash risk. This positive relationship holds firmly after addressing potential endogeneity and the performing of robustness tests. Also, the influence of monitoring quality is tested for firms with different levels of market competition and board independence. The findings of this study are meaningful because many prior studies of stock price crash risk build on the argument that management has motivations to hoard negative information. However, under the presumption of investors' behaviours, this study demonstrates that firms' business risk, proxied by productivity uncertainty, is a significant source of stock price crash risk.

The paper is organized as follows: Section 2 details the research design. Section 3 exhibits the empirical results and robustness tests. Section 4 concludes this study.

2. Research Design

2.1 Sample Description

This study uses multiple data sources to construct a comprehensive sample of publicly traded firms from 2001 to 2021. Firm fundamental data are obtained from the COMPUSTAT database. The measures of stock price crash risk are calculated by using stock performance data retrieved from the Center of Research in Security Prices (CRSP). Board information is garnered from the BoardEx database. Auxiliary data are obtained from Bloomberg and I/B/E/S database. Due to high regulation, financial firms, and utility firms (4-digit SIC 6000-6999 and 4900-4999) are excluded. For the concern of the potential impact of low liquidity, following prior studies (e.g., Hutton et al., 2009; Kim et al., 2011a, 2011b; Kim et al., 2014; Kim et al., 2016), observations are dropped for those with year-end closing stock price below $1, fewer than 26 weeks of return data, negative book value of total assets, or insufficient data entries. The finalized sample contains a number of 39,126 firm-year observations.

2.2 Measures of Productivity Uncertainty

According to Zhao and Sing (2016), a company's productivity refers to the notion of output per unit of capital. It is estimated by the cash flow from operations divided by the book value of total assets, denoted as *CFOA*. Two measures of productivity uncertainty are constructed as follows: as shown in Eq. (1) and denoted as *PUCA*, the first measure is the rolling standard deviation of a firm's *CFOA* over the last five years. Hence, companies with high productivity uncertainty would exhibit high values of *PUCA*. In order to capture the effect of potential business cycle shocks, as shown in Eq. (2) and denoted as *PUCI*, the second measure is the rolling standard deviation of a firm's time-variant productivity deviations from the industry average over the last five years, where $CFOI_{i,t} = CFOA_{i,t} - \frac{1}{N}\sum_{i=1}^{N} CFOA_{i,t}$ and *N* is the number of firms in the same industry of firm i.

$$PUCA = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(CFOA_{i,t} - \frac{1}{T}\sum_{t=1}^{T} CFOA_{i,t})^2} \tag{1}$$

$$PUCI = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(CFOI_{i,t} - \frac{1}{T}\sum_{t=1}^{T} CFOI_{i,t})^2} \tag{2}$$

2.3 Measures of Stock Price Crash Risk

Following Chen et al. (2001), Kim et al. (2011a, 2011b), and Kim et al. (2014), this study employs two well-acknowledged measures of stock price crash risk, i.e., negative conditional skewness denoted as *NCSKEW* and down-to-up volatility denoted as *DUVOL*. These two measures are both derived from firm-specific weekly returns that are calculated by using the residuals of a market model shown in Eq. (3). Specifically, a firm-specific weekly return $W_{i,\tau}$ is the natural logarithm of one plus the residual return, i.e., $W_{i,\tau} = \mathrm{Ln}\,(1+\hat{\varepsilon}_{i,\tau})$. The advantage of this approach is that it controls the influence of broad market movements and delivers the unique information of an individual firm's stock price crash risk.

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau-2} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \varepsilon_{i,\tau} \tag{3}$$

The first measure of stock price crash risk called negative conditional skewness (*NCSKEW*), as shown in Eq. (4), is calculated by using the third moment of $W_{i,\tau}$ which is normalized by the standard deviation of $W_{i,\tau}$ to the power of three, where n is the number of observations of a firm's $W_{i,\tau}$ in a given year. The negative sign is put before the mathematical expression so that a higher value of *NCSKEW* indicates higher stock price crash risk. The second measure of stock price crash risk is the down-to-up volatility (*DUVOL*) which is specified in Eq. (5). For an individual firm in a given year, its weekly returns, i.e., $W_{i,\tau}$, are classified into two groups: "down weeks" group and "up weeks" group. The "down weeks" group contains all weekly returns below the annual average and the "up weeks" group contains all weekly returns above the annual average. *DUVOL* is constructed by taking the natural logarithm of the standard deviation of $W_{i,\tau}$ of the "down weeks" group divided by the standard deviation of $W_{i,\tau}$ of the "up weeks" group. In a given year, n_d is the number of $W_{i,\tau}$ belonging to the "down weeks" group and n_u is the number of $W_{i,\tau}$ belonging to the "up weeks" group. Similar to the direction interpretation of *NCSKEW*, a higher value of *DUVOL* indicates higher stock price crash risk. Table 1 presents the summary statistics for all variables. An average firm has a stock price crash risk measure of 0.126 and -0.013 in *NCSKEW* and *DUVOL* respectively. Meanwhile, it has a productivity uncertainty measure of 0.865 and 0.824 in *PUCA* and *PUCI* respectively. The estimates are generally comparable and consistent with prior literature such as Kim et al. (2014), Kubick and Lockhart (2016), Beladi et al. (2021) with variations due to different sample selections.

Table 1: Summary Statistics

	Mean	P25	Median	P75	St. Dev.
Main variables					
NCSKEW	0.126	-0.512	0.108	0.529	1.166
DUVOL	-0.013	-0.297	-0.037	0.288	0.461
PUCA	0.865	0.026	0.079	0.136	0.125
PUCI	0.824	0.017	0.072	0.128	0.098
Control variables					
DTURN	0.019	-0.246	0.012	0.255	0.391
RET	-0.229	-0.330	-0.217	-0.115	0.766
MB	2.186	1.365	1.752	3.359	1.763
SIZE	7.628	6.643	7.531	8.672	1.689
SIG	0.059	0.037	0.056	0.725	0.030
LEV	0.179	0.006	0.141	0.275	0.181
ROA	0.077	0.011	0.095	0.163	0.156
ACCU	0.361	0.061	0.264	0.508	0.322

$$NCSKEW = -\left[n(n-1)^{3/2}\sum W_{i,\tau}^{3}\right]\Big/\left[(n-1)(n-2)\left(\sum W_{i,\tau}^{2}\right)^{3/2}\right] \quad (4)$$

$$DUVOL = Ln\left\{(n_u-1)\sum_{down} W_{i,\tau}^{2}/(n_d-1)\sum_{up} W_{i,\tau}^{2}\right\} \quad (5)$$

2.4 Methodology

To empirically test the effect of productivity uncertainty on stock price crash risk, this study specifies a multivariate regression model as the follows:

$$CRASH\_RISK_{i,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \beta_2 CRASH\_RISK_{i,t-1}$$
$$+\beta_3 DTURN_{i,t-1} + \beta_4 RET_{i,t-1} + \beta_5 MB_{i,t-1}$$
$$+ \beta_6 SIZE_{i,t-1} + \beta_7 SIG_{i,t-1} + \beta_8 LEV_{i,t-1} + \beta_9 ROA_{i,t-1}$$
$$+ \beta_{10} ACCU_{i,t-1} + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \tag{6}$$

The dependent variable *CRASH_RISK* takes two measures: the negative conditional skewness (*NCSKEW*) and the down-to-up volatility (*DUVOL*). The independent variable *PROD_UNCTY* is proxied by *PUCA* and *PUCI*. Following prior studies represented by Chen et al. (2001), Kim et al. (2011a, 2011b), Kim et al. (2014), and Dang et al. (2022), a set of control variables are defined: the one-year time-lagged *CRASH_RISK* is controlled for potential time-series correlation of the crash risk. *DTURN* measures the average difference of monthly share turnover over the last fiscal year and the year before. *RET* is the average of firm-specific weekly returns. *MB* is the market-to-book ratio, calculated by taking the ratio of market value of equity to the book value of equity. Firm size, i.e., *SIZE*, is measured by the natural logarithm of market value of equity. *SIG* is the standard deviation of firm-specific weekly returns. *LEV* represents a firm's financial leverage, calculated as the ratio of long-term debts to total assets. Return of assets, i.e., *ROA*, is computed as the income before extraordinary items divided by total assets. *ACCU* measures earnings management. It is the absolute value of abnormal accruals derived based on the modified Jones model (Dechow et al., 1995). Year fixed effects and industry fixed effects are controlled in all models.

3. Empirical Results

3.1 The Effect of Productivity Uncertainty on Stock Price Crash Risk

Table 2 presents the regression results of the relationship between productivity uncertainty and stock price crash risk. Columns 1 and 3 employ *PUCA* as the proxy for productivity uncertainty while columns 2 and 4 employ *PUCI*. Stock price crash risk takes two measures, i.e., *NCSKEW* and *DUVOL*, with each of them being regressed on *PUCA* and *PUCI* respectively. Continuous variables are winsorized at the 1st and 99th percentiles and robust standard errors are clustered at the firm-level.

As exhibited in Table 2, the results strongly suggest that a firm's productivity uncertainty is positively associated with stock price crash risk. The estimated coefficients of *PUCA* and *PUCI* are statistically significant at the 5% level or better across all models. In terms of economic significance, column 1 indicates that a one percent increase of *PUCA* leads to 0.026 increase of *NCSKEW* and column 3 shows that a one percent increase of *PUCA* leads to 0.012 increase of *DUVOL*, ceteris paribus. Additionally, columns 2 and 4 also provide very consistent and comparable results for the impact of *PUCI* on *NCSKEW* and *DUVOL* respectively. Under the presumption of the influence of investors' "information blockage effect" and "volatility feedback effect", the evidence is very supportive for the argument that firms with higher productivity uncertainty tend to exhibit greater stock price crash risk. The estimated coefficients of control variables are consistent with prior studies, e.g., Kim et al. (2014), Jebran et al. (2020), and Dang et al. (2022), suggesting that firms with higher past stock return, higher market-to-book ratio, larger size, greater stock volatility, higher ROA, and higher earnings management are associated with greater stock price crash risk.

Table 2: Effect of Productivity Uncertainty on Stock Price Crash Risk

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA_{t-1}$	0.026**		0.012**	
	(2.12)		(2.31)	
$PUCI_{t-1}$		0.033**		0.015***
		(1.98)		(3.01)
$NCSKEW_{t-1}$	0.008*	0.005		
	(1.76)	(1.61)		
$DUVOL_{t-1}$			0.002	0.002
			(1.12)	(1.35)
$DTURN_{t-1}$	0.012	0.015	0.005	0.003
	(0.52)	(0.31)	(0.66)	(0.79)
RET_{t-1}	0.046***	0.039***	0.012***	0.018***
	(3.82)	(5.26)	(2.98)	(3.31)
MB_{t-1}	0.008***	0.007***	0.003***	0.003***
	(6.82)	(7.19)	(5.56)	(5.82)
$SIZE_{t-1}$	0.018***	0.016***	0.009***	0.009***
	(8.12)	(8.96)	(9.51)	(9.26)
SIG_{t-1}	1.326**	1.256**	0.721***	0.695**
	(2.06)	(1.88)	(2.58)	(2.29)
LEV_{t-1}	-0.079	-0.083	-0.036	-0.032
	(0.26)	(0.31)	(0.61)	(0.55)
ROA_{t-1}	0.296***	0.281**	0.156**	0.161**
	(2.88)	(2.15)	(1.97)	(2.08)
$ACCU_{t-1}$	0.005*	0.006*	0.002*	0.002**
	(1.75)	(1.69)	(1.88)	(1.96)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table shows the regressions results of stock price crash risk on productivity uncertainty. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.2 Addressing Endogeneity

The positive relationship between productivity uncertainty and stock price crash risk may be affected by potential endogeneity. Hence, it is imperative to use econometric methods to address this concern. This study employs two approaches, i.e., two-stage least square regressions and first-difference regressions, to retest the relationship between productivity uncertainty and stock price crash risk. Following prior studies, e.g., El Ghoul et al. (2011), Lin et al. (2013), Kim et al. (2014), two instrumental variables (IV) are individually constructed as follows for productivity uncertainty measures: *IND_PUCA* = $\sum_{j=1}^{M} \frac{PUCA_j}{M}$ and *IND_PUCI* = $\sum_{j=1}^{M} \frac{PUCI_j}{M}$ where M is the number of firms in the same Fama-French 48 industry. The meaning of these two instrumental variables is straightforward as they represent the average productivity uncertainty in the same industry. They are ideal IVs because a firm's productivity uncertainty is considered to be vastly correlated with the industry average. Nevertheless, a firm's stock price crash risk is largely influenced by its own productivity uncertainty. Hence, *IND_PUCA* are *IND_PUCI* should be strictly exogenous.

Table 3: Two-stage Least Square Regressions to Address Endogeneity

Panel A. First stage: instrumenting productivity uncertainty		
	(1) **PUCA**	**(2)** **PUCI**
IND_PUCA	0.926*** (6.29)	
IND_PUCI		0.895*** (8.61)
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
F-statistic	36.65	42.92

Panel B. Second stage: coefficients of 2SLS regressions				
	(1) **$NCSKEW_t$**	**(2)** **$NCSKEW_t$**	**(3)** **$DUVOL_t$**	**(4)** **$DUVOL_t$**
$PUCA_{t-1}$	0.046** (2.06)		0.021* (1.89)	
$PUCI_{t-1}$		0.051** (2.28)		0.027** (2.51)
$NCSKEW_{t-1}$	0.006 (1.51)	0.003* (1.69)		
$DUVOL_{t-1}$			0.001 (0.98)	0.001 (0.91)
$DTURN_{t-1}$	0.010 (0.86)	0.012 (0.42)	0.003 (0.76)	0.002 (0.85)
RET_{t-1}	0.068*** (3.12)	0.053*** (4.96)	0.019*** (2.82)	0.018*** (2.99)
MB_{t-1}	0.015*** (7.32)	0.012*** (7.72)	0.005*** (6.82)	0.006*** (7.01)
$SIZE_{t-1}$	0.018*** (8.12)	0.016*** (8.96)	0.009*** (9.51)	0.009*** (9.26)
SIG_{t-1}	1.891*** (2.67)	1.685** (2.27)	1.126** (2.21)	1.092** (2.21)
LEV_{t-1}	-0.112 (0.32)	-0.126 (0.45)	-0.051 (0.89)	-0.045 (0.72)
ROA_{t-1}	0.198** (2.39)	0.212* (1.92)	0.109* (1.79)	0.132** (1.97)
$ACCU_{t-1}$	0.072** (2.06)	0.085** (2.39)	0.019* (1.91)	0.015** (1.82)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.028	0.025	0.039	0.032

*Note: This table displays the results of 2SLS regressions to address endogeneity. IND_PUCA and IND_PUCI are the two instrumental variables defined as the averages of PUCA and PUCI in the same Fama–French 48 industry respectively. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3 displays the results of the two-stage least square regressions. As shown in Panel A, the first stage instruments the measures of productivity uncertainty by regressing them on instrumental variables along with other control variables. The estimated coefficients of *IND_PUCA* and *IND_PUCI* are both statistically significant at the 1% level. Also, the associated F-statistics are well above 10, suggesting that both instrumental variables are statistically strong. The second stage regresses *NCSKEW* and *DUVOL* on the fitted values of *PUCA* and *PUCI* obtained from the first stage while controlling all control variables. The corresponding estimated coefficients are significant at the 5% level in columns 1, 2, and 4 with a significance of 10% level in column 3. In summary, the results of Table 3 indicate that the positive relationship between productivity uncertainty and stock price crash risk holds firmly after implementing the instrumental variable approach.

Table 4: First-difference Regressions to Address Endogeneity

	(1) $\Delta NCSKEW_t$	(2) $\Delta NCSKEW_t$	(3) $\Delta DUVOL_t$	(4) $\Delta DUVOL_t$
$\Delta PUCA_{t-1}$	0.038** (2.06)		0.018** (2.20)	
$\Delta PUCI_{t-1}$		0.029* (1.88)		0.020** (2.12)
$\Delta NCSKEW_{t-1}$	0.003 (1.51)	0.007 (1.33)		
$\Delta DUVOL_{t-1}$			0.001 (0.99)	0.002 (1.05)
$\Delta DTURN_{t-1}$	0.009 (0.38)	0.011 (0.42)	0.008 (0.41)	0.008 (0.60)
ΔRET_{t-1}	0.021*** (2.86)	0.018** (1.99)	0.010* (1.83)	0.013** (2.39)
ΔMB_{t-1}	0.002 (1.52)	0.003* (1.66)	0.001* (1.70)	0.001 (1.17)
$\Delta SIZE_{t-1}$	0.015* (1.91)	0.014** (2.07)	0.011* (1.85)	0.010* (1.77)
ΔSIG_{t-1}	0.882*** (2.72)	0.797** (2.49)	0.593** (1.98)	0.608*** (3.12)
ΔLEV_{t-1}	0.069 (0.33)	0.059 (0.57)	0.021 (0.29)	0.046 (0.38)
ΔROA_{t-1}	0.127* (1.69)	0.136* (1.75)	0.097** (2.28)	0.102 (1.53)
$\Delta ACCU_{t-1}$	0.008 (1.39)	0.010* (1.80)	0.001 (1.26)	0.002 (0.93)
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.039	0.042	0.059	0.061

*Note: This table presents the results of first-difference regressions to address endogeneity. All variables are first-differenced to capture the year-over-year temporal changes (Δ denotes the first-difference operator). Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Moreover, to perform the first-difference regressions, all variables are first-differenced so that the year-over-year temporal changes are captured. Table 4 presents the regression results in which Δ denotes the first-difference operator. The estimated coefficients of *ΔPUCA* and *ΔPUCI* are positively significant at 10% level or better across all columns. The results confirm that the positive relationship between productivity uncertainty and stock price crash risk is evident.

3.3 The Channel Effect of Implied Cost of Equity Capital

As discussed previously, the positive relationship between firms' productivity uncertainty and stock price crash risk is based on the presumption of "information blockage effect" and "volatility feedback effect" (e.g., Cao et al., 2002; Hong & Stein, 2003; Wu, 2001; Carr and Wu, 2017). Although these two theories are from different perspectives to model investors' behaviors, they all support the notion that investors are risk-averse and constantly adjust their risk assessment when information is presented. Since productivity uncertainty reflects a firm's business risk, the information should be captured by the implied cost of equity capital which serves as a channel for investors to exhibit their risk premium sentiment (e.g., Gay et al., 2011; Huber and Huber, 2019; Balakrishnan et al., 2021).

To test this channel effect, following Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), this study constructs four measures of implied cost of equity capital (denote R_{GLS}, R_{CT}, R_{OJ}, and R_{MPEG} respectively. See Appendix for details). These measures are derived based on analysts' earnings forecasts which serve as the main venues for investors' assessment on firms' riskiness. In general, risky firms tend to have higher implied cost of equity capital and vice versa. The average of the four measures (denote R_{ICEC}) minus the risk-free rate is used for regression analysis to avoid potential deviation caused by a single estimate (e.g., Ghoul et al., 2011; Chen et al., 2011). Two multivariate regression models are specified below. Eq. (7) is used to test the statistical significance of productivity uncertainty on the mediator. Subsequently, Eq. (8) is designed to reveal the channel effect by examining the mediation role of implied cost of equity capital on stock price crash risk. All control variables follow the same definitions as described in section 2.4.

$$R_{ICECi,t} - R_{f,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \sum CONTROLS + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \quad (7)$$

$$CRASH\_RISK_{i,t} = \beta_0 + \beta_1 PROD\_UNCTY_{i,t-1} + \beta_2 (R_{ICEC} - R_f)_{i,t-1} + \sum CONTROLS + \gamma_{year} + \mu_{ind} + \varepsilon_{i,t} \quad (8)$$

Table 5 presents the empirical results for the channel effect of implied cost of equity capital. Panel A. shows that both *PUCA* and *PUCI* are positively and significantly associated with $R_{ICEC} - R_f$. This is the prerequisite for the mediation role and it demonstrates that firms with high productivity uncertainty tend to have high implied cost of equity capital. Panel B. confirms the channel effect as the estimated coefficient of the mediator, i.e., $R_{ICEC} - R_f$, is significant across all models. It is important to note that the coefficient magnitude and statistical significance of *PUCA* and *PUCI* are diminished as compared with those in Table 2, which validates the channel effect.

Table 5: Channel Effect of Implied Cost of Equity Capital

Panel A. Association between productivity uncertainty and mediator		
	(1)	(2)
	$R_{ICEC} - R_f$	$R_{ICEC} - R_f$
PUCA	0.239*** (3.08)	
PUCI		0.305** (2.36)
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel B. Mediation of implied cost of equity capital on stock price crash risk				
	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA_{t-1}$	0.018**		0.009*	
	(2.01)		(1.89)	
$PUCI_{t-1}$		0.027*		0.013**
		(1.79)		(2.52)
$(R_{ICEC} – R_f)_{t-1}$	0.012**	0.010**	0.007***	0.005*
	(2.25)	(1.99)	(2.67)	(1.68)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.060	0.055	0.071	0.067

*Note: This table presents the regression analysis for the channel effect of implied cost of equity capital. RICEC is the average of RGLS, RCT, ROJ, and RMPEG. See Appendix for detailed definitions. Rf is the risk-free rate. PUCA, PUCI, NCSKEW, and DUVOL are defined in section 2.2 and 2.3. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.4 The role of market competition and board independence

From the perspective of agency cost, previous literature argues that management has incentives to hoard negative information for extended periods of time. This type of behaviour causes the buildup of negative information, which leads to the subsequent stock price crash (e.g., Hutton et al., 2009; Kothari et al., 2009). Therefore, if this argument holds, then monitoring quality should make a difference in stock price crash risk, because managers of firms with good monitoring aren’t able to withhold bad news easily or for a long period of time, and vice versa. Prior studies indicate that monitoring quality is affected by two important factors, i.e., market competition and board independence. Baggs and De Bettignies (2007) and Giroud and Mueller (2010, 2011) suggest that market competition mitigates agency cost by serving as a form of monitoring. Firms in non-competitive markets or industries have weaker corporate governance and less information transparency. On the other hand, Setia-Atmaja et al. (2011), Bradley and Chen (2015), and Fuzi et al. (2016) collectively suggest that a higher degree of board independence is associated with better monitoring, which can improve firm performance and better align the interests of management and shareholders. Therefore, the effect of productivity uncertainty on stock price crash risk should be stronger for firms with weak market competition or a low degree of board independence, since those firms are subject to weak monitoring and low efficiency in flow of information. To empirically test this argument, two dummy variables are defined as follows: for the measure of market competition, *HHI_Hi* equals one if a firm’s Herfindahl-Hirschman Index (HHI) is above the sample median in a given year, and zero otherwise. Since a high Herfindahl-Hirschman Index means a high market concentration, *HHI_Hi* with a value of one indicates a low degree of market competition; for the measure of board independence, *BRDIN_Hi* equals one if a firm’s board independence ratio, i.e., the number of independent directors divided by the total number of directors, is above the sample median in a given year, and zero otherwise. *BRDIN_Hi* with a value of one indicates a high degree of board independence. As shown in Table 6, regression results show that the effect of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition in terms of both statistical and economic significance. The estimated coefficients of the measures of productivity uncertainty interacted with *HHI_Hi* are significant at the 5% level or better. However, those that interacted with *1-HHI_Hi* display lower levels of significance. Regarding the magnitude of the effect, e.g., column 1, on average one percent increase of *PUCA* leads to 0.031 increase of *NCSKEW* for firms with weak market competition, ceteris paribus. In comparison, this effect diminishes to 0.02 for firms with strong market competition. On the other hand, as shown in Table 7, the effect of productivity uncertainty on stock price crash risk is more pronounced for firms with less independent boards. In general, the estimated coefficients of those interacted with

1-BRDIN_Hi exhibit higher levels of significance. Regarding the magnitude of the effect, e.g., column 1, on average one percent increase of *PUCA* leads to 0.029 increase of *NCSKEW* for firms with less independent boards, ceteris paribus. In contrast, this effect lowers to 0.023 for firms with more independent boards.

Table 6: Regression Analysis of the Influence of Market Competition

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA*(1-HHI\_Hi)_{t-1}$	0.020*		0.009**	
	(1.79)		(2.03)	
$PUCA*HHI\_Hi_{t-1}$	0.031***		0.016***	
	(3.29)		(3.65)	
$PUCI*(1-HHI\_Hi)_{t-1}$		0.028*		0.013*
		(1.71)		(1.86)
$PUCI*HHI\_Hi_{t-1}$		0.039**		0.018***
		(2.39)		(4.05)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table presents the results of regression analysis for the influence of market competition on the effect of productivity uncertainty on stock price crash risk. HHI_Hi is a dummy variable that equals one if a firm's Herfindahl-Hirschman Index (HHI) is above the sample median in a given year, and zero otherwise. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

Table 7: Regression Analysis of the Influence of Board Independence

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCA*(1-BRDIN\_Hi)_{t-1}$	0.029**		0.015***	
	(2.31)		(2.69)	
$PUCA*BRDIN\_Hi_{t-1}$	0.023*		0.010*	
	(1.88)		(1.75)	
$PUCI*(1-BRDIN\_Hi)_{t-1}$		0.037**		0.017***
		(2.16)		(3.55)
$PUCI*BRDIN\_Hi_{t-1}$		0.030*		0.011**
		(1.68)		(2.36)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.056	0.052	0.068	0.065

*Note: This table presents the results of regression analysis for the influence of board independence on the effect of productivity uncertainty on stock price crash risk. BRDIN_Hi is a dummy variable that equals one if a firm's board independence ratio is above the sample median in a given year, and zero otherwise. As defined in section 2.2 and 2.3, independent variable is measured by PUCA and PUCI and dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

3.5 Robustness check

For the examination of robustness, two alternative measures of productivity uncertainty are employed based on prior studies. Following Daniel et al. (2008) and Deng et al. (2013), *PUCS* is defined as the cash flow short fall divided by total assets, where cash flow short fall equals to the expected investment plus expected dividend then minus available cash flow. Following Jayaraman (2008) and Chaya and Suh (2009), *PUCV* is defined as the operating profit volatility, which is estimated by calculating the standard deviation of operating rate of return. These two measures assess productivity uncertainty from different cash flow perspectives, but both of them gauge the riskiness of output on a per unit of asset basis. Table 8 shows the regression results of robustness tests. The estimated coefficients of *PUCS* and *PUCV* are significant at the 5% level or better across all models. The results are very consistent with the outcome of the main regression, confirming that productivity uncertainty is positively associated with stock price crash risk.

Table 8: Robustness Tests Using Alternative Measures of Productivity Uncertainty

	(1) $NCSKEW_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $DUVOL_t$
$PUCS_{t-1}$	0.021**		0.007***	
	(2.29)		(2.61)	
$PUCV_{t-1}$		0.029**		0.008**
		(2.36)		(2.39)
$NCSKEW_{t-1}$	0.011	0.015*		
	(1.59)	(1.82)		
$DUVOL_{t-1}$			0.005	0.006*
			(1.52)	(1.69)
$DTURN_{t-1}$	0.016	0.018	0.001	0.002
	(0.31)	(0.12)	(0.81)	(0.92)
RET_{t-1}	0.031***	0.036***	0.021***	0.026***
	(4.11)	(4.75)	(3.16)	(3.51)
MB_{t-1}	0.010***	0.012***	0.002***	0.001***
	(5.85)	(6.09)	(5.12)	(4.96)
$SIZE_{t-1}$	0.015***	0.012***	0.006***	0.005***
	(8.53)	(8.66)	(9.75)	(9.31)
SIG_{t-1}	1.105*	1.182**	0.787***	0.751***
	(1.92)	(2.00)	(2.72)	(2.63)
LEV_{t-1}	-0.068	-0.077	-0.029	-0.030
	(0.35)	(0.46)	(0.55)	(0.551)
ROA_{t-1}	0.316**	0.302**	0.168**	0.179**
	(2.41)	(2.28)	(2.02)	(2.16)
$ACCU_{t-1}$	0.005*	0.006	0.001*	0.002*
	(1.69)	(1.58)	(1.81)	(1.90)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	39,126	39,126	39,126	39,126
Adj. R-squared	0.057	0.055	0.062	0.061

*Note: This table presents the results of robustness tests using two alternative measures of productivity uncertainty, i.e., PUCS and PUCV. Dependent variable is measured by NCSKEW and DUVOL. Control variables are defined in section 2.4 and continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm-level. The t-statistics are reported in the parentheses. ***, **, and * represent significance at the 1%, 5% and 10% levels respectively.*

4. Conclusion

This study examines the impact of productivity uncertainty on stock price crash risk. A firm's business risk is captured by its productivity uncertainty. Under the presumption of investors' information blockage effect and volatility feedback effect, stock returns of firms with higher productivity uncertainty should exhibit greater negative skewness, i.e., higher stock price crash risk. The empirical results of this study support this argument by showing that there is a significantly positive association between productivity uncertainty and stock price crash risk. This result holds firmly after addressing for potential endogeneity and the performing of robustness tests. The examination of channel effect further suggests that firms' implied cost of equity capital serves as a mediator that facilitates the information transmission of productivity uncertainty to the stock market. Moreover, this study also examines the influence of monitoring quality in terms of market competition and board independence. Consistent with the explanation based on agency cost, the positive impact of productivity uncertainty on stock price crash risk is more pronounced for firms with weak market competition and less independent boards.

Appendix

Measures of implied cost of equity capital

Notation	Formula	Reference
R_{GLS}	$P_t = B_t + \sum_{k=1}^{11} \frac{E_t[(ROE_{t+k} - R_{GLS}) \times B_{t+k-1}]}{(1 + R_{GLS})^k} + \frac{E_t[(ROE_{t+12} - R_{GLS}) \times B_{t+11}]}{R_{GLS} \times (1 + R_{GLS})^{11}}$	Gebhardt et al. (2001)
R_{CT}	$P_t = B_t + \sum_{k=1}^{5} \frac{E_t[(ROE_{t+k} - R_{CT}) \times B_{t+k-1}]}{(1 + R_{CT})^k} + \frac{E_t\{[(ROE_{t+5} - R_{CT}) \times B_{t+4}] \times (1 + g_l)\}}{(R_{CT} - g_l) \times (1 + R_{CT})^5}$	Claus and Thomas (2001)
R_{OJ}	$R_{OJ} = A + \sqrt{A^2 + \frac{E_t(EPS_{t+1})}{P_t} \times (g_s - g_l)}$ where $A = 0.5 \times [g_l + \frac{E_t(DPS_{t+1})}{P_t}]$	Ohlson and Juettner-Nauroth (2005)
R_{MPEG}	$P_t = \frac{E_t(EPS_{t+2}) + R_{MPEG} \times E_t(DPS_{t+1}) - E_t(EPS_{t+1})}{R_{MPEG}^2}$	Easton (2004)

Note: P_t is the market share price; B_t is the book value of equity; E_t is the expectation operator; ROE is the return on equity forecast; EPS and DPS are earnings per share and dividends per share forecasts; g_s is the short-term EPS growth rate forecast; g_l equals the contemporary 10-year T-bond yield minus 3%.

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COUNTRY-SPECIFIC INVESTOR ATTENTION AND ADR MISPRICING

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Abstract

This paper examines the effect of country-specific investor attention on ADR mispricing. Investor attention is measured by the amount of traffic a country's Wikipedia profile page receives. A two-stage least squares (2SLS) regression is employed to examine the relationship between investor attention and ADR mispricing, but also to mitigate endogeneity between the two variables of interest. We use the FIFA World Ranking (country soccer ranking) and the number of UNESCO heritage sites as instruments for investor attention, given the unlikelihood that either of those variables can be caused by ADR mispricing. Our results show that lower levels of investor attention lead to higher ADR mispricing, therefore leading to greater divergence of the law of one price for the sample of ADRs. The results are robust across various model specifications and to well-known determinants of mispricing such as turnover, stock prices, exchange rates, and market capitalisation.

JEL: G14, G15, G40

Keywords: American Depository Receipts, Investor Attention, Wikipedia Page Views

1. Introduction

American Depositary Receipts (ADRs) are financial instruments traded in the U.S. representing ownership in foreign publicly traded firms. ADRs are generally issued by U.S. banks. Many ADRs are publicly traded in American stock markets, such as the New York Stock Exchange and the NASDAQ. They are often seen as a convenient vehicle for U.S. investors who seek to diversify their portfolios internationally. ADRs remove the major inconvenience of having to purchase the shares directly in foreign stock markets (e.g., converting dollars to a foreign currency or establishing a brokerage account offshore). According to the law of one price, ADRs and their underlying stocks should converge to one price after accounting for exchange rates and transaction costs (Kato et al., 1990). This convergence is because the real asset (the firm) is expected to generate the same future stream of cash flows for both financial assets (i.e., the ADR and the foreign-listed stock).

Although ADRs should reflect the underlying security's price behaviour, it is not uncommon to see deviations from the price-parity condition that is expected from the law of one price. These deviations can have a positive or negative value, for which they are commonly referred to as premiums or discounts, respectively. This phenomenon is known in the literature as ADR mispricing. The study of ADR mispricing is particularly relevant for traders who may benefit from these price deviations, as Suarez (2005) shows. There is a debate in the literature on whether ADR mispricing exists. Early findings suggest that there is no mispricing on cross-listed securities, therefore, it is not possible for arbitrageurs to benefit.

For instance, Rosenthal (1983) examined the weak form efficiency of ADRs from 1974–1978. He showed that weak form efficiency is supported by the serial correlation and ran tests for a sample of NASDAQ ADRs. Later, Kato et al. (1990) also found evidence in favour of the law of one price in their study of foreign stocks from Australia, England, and Japan. They observed no significant difference between the ADR and the underlying stock's price; they attributed the small differences in the return correlation to differences in market timing. Also, Lamont & Thaler (2002) argue that limits to arbitrage can prevent the law of one price to hold and, hence, force ADRs to exhibit significant deviations (premiums and discounts) from their underlying securities.

More recent studies have found that ADR mispricing exists, and it is possible for investors to benefit from arbitrage opportunities (Wahab et al., 1993; Suarez, 2005; and Ansotegui et al., 2013). However, the factors that drive the mispricing are still being debated in the literature. For example, Foerster and Karolyi (2000) showed that investment barriers account for the long-run difference in the performance of cross-listed firms. Furthermore, Maldonado and Saunders (1983) argued that such barriers represent an arbitrage opportunity for unrestricted investors, while Kadiyala and Subrahmanyam (2004) determined that ADRs from countries with foreign ownership restrictions are sold at a premium of around 11.33%, with respect to their underlying foreign shares. Similarly, Arquette et al. (2008) found that expected currency appreciation in Chinese cross-listed stocks has a negative effect on the discounts of a sample of both ADRs listed on the NYSE and H-Shares listed in Hong Kong. According to Hsu and Wang (2008), trading volume and macroeconomic events generate heterogeneous expectations between the home and foreign markets, which might explain the premia (or discounts) observed in the data. Chan et al. (2008) showed that higher levels of liquidity in the ADR, with respect to its underlying share, lead to a higher premium.

Another stream of the mispricing literature attributes deviations from the price-parity condition to investor sentiment. Grossmann et al. (2007) looked at a sample of ADRs from nine countries and determined that transaction costs, lower dividend payments, and the difference in consumer sentiment (a proxy for investor sentiment) of the U.S. and the home country influence ADR mispricing. Hwang (2011) studied the effect of country-specific sentiment on ADR mispricing. He found that country popularity among U.S. investors is also responsible for deviations from the price-parity condition for ADRs. More recently, Beckmann et al. (2015) attributed ADR mispricing to information asymmetry with regard to the underlying stock, along with freedom scores of the home country, listing level and idiosyncratic risk. Finally, Wu et al. (2017) examined the effect of local and global investor sentiment on mispricing and found that idiosyncratic risk is an important determinant.

Recently, investor attention in stock markets has played a greater role in the finance literature. For example, Barber and Odean (2008) showed that individual investors are overwhelmed by the amount of investment options. As a result, they make their investment choices based on preference after their limited attention has put together their choice set. Van Nieuwerburgh and Veldkamp (2010), showed that the selection of risky assets depends on the assets the investor possesses information about. Moreover, the use of Wikipedia as a tool to gauge investor attention has also been established in the literature. For example, Kristoufek (2013), studied the effect of Google Trends and Wikipedia searches on Bitcoin prices; this study determined that there is an asymmetric effect with spikes in interest; he also suggests that people might search for countries on Wikipedia to learn more about their economic phenomena, such as the value of digital currencies. Also, Gozzi et al. (2020), utilised COVID-19 Wikipedia pages as a proxy for public attention to model and predict public response to media coverage and epidemic progression. This study indicates that people may search for countries on Wikipedia in response to media coverage of events happening in those countries. Moreover, Corwin and Coughenour (2008) show that limited attention to actively traded stocks results in infrequent price adjustments and increased transaction costs to less noticed stocks.

Eichler (2012) examined the relationship between investor attention and ADR mispricing. He used the number of times internet users visited websites domiciled in a particular country as a proxy for investor attention. His study used a sample of 537 ADRs for a period of three months. Eicher (2012) showed that a higher degree of investor attention leads to lower levels of ADR mispricing for the sample of 537

ADRs. Mondria et al. (2010) showed that when U.S. investors' equity home bias is lower, the more attention they pay to a foreign country's stock. Tang and Zhu (2017) studied how increases in SVIs are related to contemporary abnormal returns for a set of ADRs, implying that higher levels of attention are associated with higher returns. One of the first studies in finance literature to use Wikipedia page views information was Moat et al. (2013). This new dataset showed the predictive power of Wikipedia page views for stock returns during the Great Recession. Da et al. (2011) used the Search Volume Indices (SVI) from Google to show that increases in the searches for companies are related to a subsequent stock price increase after two weeks. Recently, Gutierrez Pineda and Perez (2021), showed that ADR's respond to changes in a high-frequency U.S. investor sentiment, similar to U.S. stocks.

Over the past few years, household internet usage data has become increasingly important and useful for scholarly research. The growth and relevance of the internet in our day-to-day activities represents a unique opportunity to observe trends and learn about the dynamics of investors' attention. Thanks to initiatives such as Google Trends and Wikipedia Trends, it is now possible to collect data from aggregated users' search history and discover its informational content for financial assets and markets, among other things.

More specifically, in this study, we argue that Wikipedia's country page views constitute a better measure of investor attention compared to the ones used in previous studies (Eichler, 2012; Mao & Wei, 2013). While this paper employs a direct measure of country-specific investor attention, past literature either use a search volume index (SVI), as in Mao and Wei (2013), or the number of clicks on search engine results from websites hosted in a particular country (Eichler, 2012; Mao & Wei, 2013). The main problem with Mao and Wei (2013) is that observations are scaled in proportion to a specific country and time span, which does not allow for an unbiased cross-country study. For Eichler (2012), the limitation is that several websites are hosted on foreign servers and the well-known practice of geographically tailored websites, which may lead to misrepresentative results. We obtain the number of times that internet users open a country's profile page on Wikipedia and use it as a proxy for investor attention to a country's ADRs. The choice of this proxy is based on Wikipedia's unquestionable position as the most popular encyclopedia freely available on the internet. The reliability and credibility of Wikipedia as a source of information is not relevant for the purpose of this study, but its popularity among users is.[1]

This paper contributes to the literature on investor attention and ADR mispricing in the following distinct ways. First, using a two-stage least squares (2SLS) regression, we test whether investor attention (proxied by Wikipedia country-profile page views) impacts overall ADR mispricing for a large set of ADRs. To the best of our knowledge, this is the first study that examines the influence of Wikipedia country page views (our proxy for investor attention) on ADR mispricing. Furthermore, our dataset of ADRs includes a larger sample size compared to prior studies (Eichler, 2012) and spans from 2008 to 2014. One benefit of this sample period is that it allows us to examine if the Great Recession had an influence on the relationship between investor attention and ADR mispricing. Second, we test whether the influence of investor attention differs for Level I ADRs or Level II and Level III ADRs.[2] Finally, we briefly examine the role of investor attention across a variety of ADR industries (e.g., telecommunications, technology, industrials, consumer services, basic materials). This allows us to see if the influence of investor attention on mispricing is sector-specific, something prior studies have not accounted for.

[1] According to Alexa.com and Similarweb.com, two popular internet traffic measuring companies, Wikipedia stands as the 5th and 12th website with most daily visits on the internet, respectively. More information can be found on https://www.similarweb.com/website/wikipedia.org and https://www.alexa.com/siteinfo/wikipedia.org.

[2] American Depositary Receipts (ADR) are classified in Levels I, II, and III. Level I ADR's are typically traded over-the-counter (OTC) and are not required to comply with many of the reporting regulations enforced by the Securities and Exchange Commission (SEC) applicable to U.S. companies. On the other hand, Level II and Level III ADRs need to comply with all these regulations, including SEC Form 20, GAAP reporting, Sarbanes-Oxley Act, etc. The main difference between level II and level III is the ability to raise capital through public offerings.

Overall, the results from the various 2SLS models show that a higher level of investor attention leads to a lower level of ADR mispricing. In other words, many Wikipedia country-profile page views are associated with a lower ADR mispricing for a sample of 1,840 cross-listed securities from 31 countries. Additionally, when we *separate* ADRs by level (i.e., Level I versus Level II and III), the findings indicate that the impact of investor attention on ADR mispricing is determined by the level of ADR. For instance, we show that investor attention has a greater impact on Level I ADRs relative to Level II and III ADRs. Moreover, our results show that the Great Recession has an impact on how investor attention influences ADR mispricing. For instance, the crisis dummy variable is larger for Level I ADRs than for levels II and III. Our study also shows that investor attention influences ADR mispricing across industries. For example, higher levels of investor attention reduced ADR mispricing for the consumer services industry. However, not all industries were influenced by investor attention (e.g., consumer goods, financials, and utilities). Overall, this study sheds new light on how investor attention influences ADR mispricing.

The remainder of the paper is organised as follows. Section 2 discusses the data and methodology. Section 3 presents the empirical findings, and Section 4 concludes.

2. Data and Methodology

This study employs two-stage least squares (2SLS) regressions using monthly data from January 2008 to December 2014. The data on ADRs is obtained from DataStream. The country-specific investor attention measure, Wikipedia country page views, is obtained from the Wikipediatrends.com website. The sample consists of 1,840 unique ADRs, from 31 countries[3], for a total of 130,788 firm-month observations. We limit this study to include only countries for which the date range and country profile page views measure was available through Wikipediatrends.com[4]. The remaining countries are China, Switzerland, United Kingdom, Spain, South Africa, Australia, Denmark, Taiwan, Italy, Germany, Philippines, Japan, Belgium, Indonesia, France, Norway, Sweden, Netherlands, Israel, Mexico, Ireland, Finland, Chile, Russia, Brazil, Argentina, Colombia, Peru, India, Greece, South, and Korea. We include all available ADR's that traded over this period of time for which information is available in our source.

We compute ADR mispricing based on Eichler (2012). He estimates an absolute mispricing measure that is calculated as the percentage deviation of the ADR price from the price implied by the home-country's underlying stock:

$$ADR\ mispricing_{it} = \left|\frac{ADR\ price_{it} - Underlying\ stock\ price_{it}}{Underlying\ stock\ price_{it}}\right| \quad (1)$$

where the ADR price (in U.S. dollars) of firm *i,* in month *t* is adjusted by the ADR ratio[5] (number of foreign shares represented by one ADR) and the underlying stock price of firm *i* in month *t* is converted from its local currency to U.S. dollars. We winsorize the mispricing data at the 5% level, (2.5% on each tail)

[4] The country Turkey was purposedly omitted due to being a homonym with the animal.
[5] ADRs are sometimes offered in a ratio different than the underlying security, that is, one ADR may be equivalent to one or multiple shares of the foreign company and vice versa, as listed in their original market. We cross compare the data to adjust for these ratios by looking at different sources besides DataStream.

to remove extreme values, outliers, and ADR's that have missing or mismatching ratio adjustments. ADR's that show stale prices over multiple months are also removed[6].

Our study lies at the intersection of the work of Hwang (2011), who shows that country-specific popularity is relevant for ADR mispricing, and the work of Eichler (2012), who finds that investor attention is also a determinant of mispricing. Therefore, our main hypothesis is that more investor attention leads to less mispricing of ADRs relative to the price of the underlying shares. As a result, we expect our model to find an inverse relationship between investor attention and ADR mispricing, which is theoretically consistent with the idea that less arbitrage opportunities exist when investors pay more attention (scrutiny) to a security from a more popular country, and vice-versa.

The investor attention measure, Wikipedia country page views, is the number of times that internet users open a country's profile page on Wikipedia. We adopt this measure as a proxy for investor attention for a country's ADRs. We consider this to be a better proxy than the ones from the previous literature because it is not subject to scaling biases (e.g., proxies using search volume indices) or foreign-host website bias (e.g., proxies that ignore that a country's webpage may be hosted by foreign country's servers). Moreover, our study spans seven years of monthly observations and includes 1,840 ADRs, including Level I ADRs, which are known to possess greater information asymmetry and therefore exhibit higher mispricing.

We anticipate that the search for information related to a particular country can be triggered by either positive or negative news. For example, the views of Brazil's page spiked during the 2014 Soccer World Cup, which can be considered a positive event overall, but the same peaks of interest occur when negative events happen (e.g., earthquakes, terrorist attacks, economic collapses). Therefore, the purpose of this study is not to clarify whether interest in each country corresponds to a premium (discount), but to assess the high (low) level of mispricing generated by investors' country-specific attention as a mechanism to obtain and reduce information asymmetry. In that sense, an investor seeking more information about a particular country on the internet will be prone to learn more about the country's ADRs. The natural consequence of doing so is that by learning more about a country, information asymmetry is narrowed and as a result price discrepancy should be smaller. It is also worth noting that Wikipedia country profiles display a section with condensed economic information such as overall economic policy, gross domestic product, unemployment, main industries, and significant mergers. Information that could be used by investors as a *prima facie* step into finding securities from that country or, in this case, ADRs.

Figure 1 displays some of the countries with the highest and lowest levels of ADR mispricing expressed in percentages. The figure shows that the highest levels of ADR mispricing correspond to the countries with the smallest numbers of Wikipedia views such as Greece (above 55% mispricing in 2012 with only 56.4 million Wikipedia views), Russia (above 35% mispricing in 2009 against 100.5 million views), and Argentina (above 32% mispricing in 2013 vs. 52.7 million views). At the same time, we observe that the lowest levels of ADR mispricing are from countries that have the largest numbers of Wikipedia views such as the United Kingdom (less than 8% mispricing in 2010 against 3.6 billion Wikipedia views) and Japan (6% mispricing in 2010 vs. 3.0 billion views) as shown in Figure 2.[7]

As Eichler (2012) points out, there could be a potential endogenous relationship between ADR mispricing and investor attention. In other words, it's plausible that the degree of mispricing in ADR's could trigger a spike in interest on a certain country which could naturally impact the number of Wikipedia country profile page views. Therefore, we control for endogeneity by estimating a two-stage least squares (2SLS) regression model:

[6] It is important to mention that many Level I ADRs are traded over the counter (OTC) and the data sometimes offers incongruencies and/or misleading values.

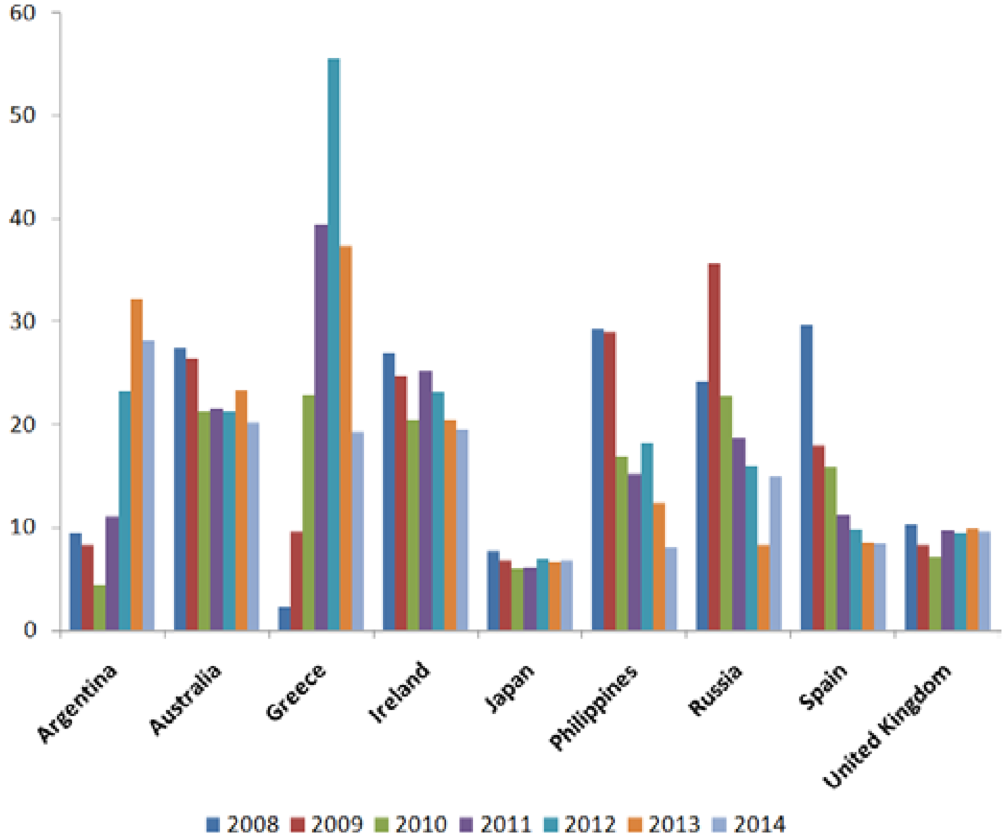
[7] Figures 1 and 2 report the ADR mispricing levels and Wikipedia views (respectively) of selected countries, which have much greater (lower) levels than average.

$$ln(investor\ attention)_i = \pi 0 + \pi_1' Z + \pi_2' X + v_i, \qquad (2)$$

$$ADR\ mispricing_i = \alpha + \beta_1 \ln(investor\ attention)_i + \beta_2' X + u, \qquad (3)$$

where the dependent variable in the first-stage regression is $investor\ attention$, $\pi R_0 R$ is a constant, v_i is the residual and Z is a vector of instrumental variables (IVs). The 2SLS regression model is a statistical method that addresses endogeneity concerns where the dependent variable might influence the independent variable. This is achieved using instrumental variables that are expected to be correlated with the endogenous variable. The fitted values of this first stage are now regressed on the dependent variable. We expect these instruments and their residuals to influence the dependent variable, but the contrary is unlikely to be true. Similar to Eichler (2012), we use the FIFA World Cup ranking score of a country's national soccer team and the number of United Nations World Heritage sites as instrument variables for investor attention. We assume these instruments to be exogenous since we cannot imagine reverse causation from ADR mispricing to the performance of a national soccer team or the number of heritage sites declared by the United Nations.

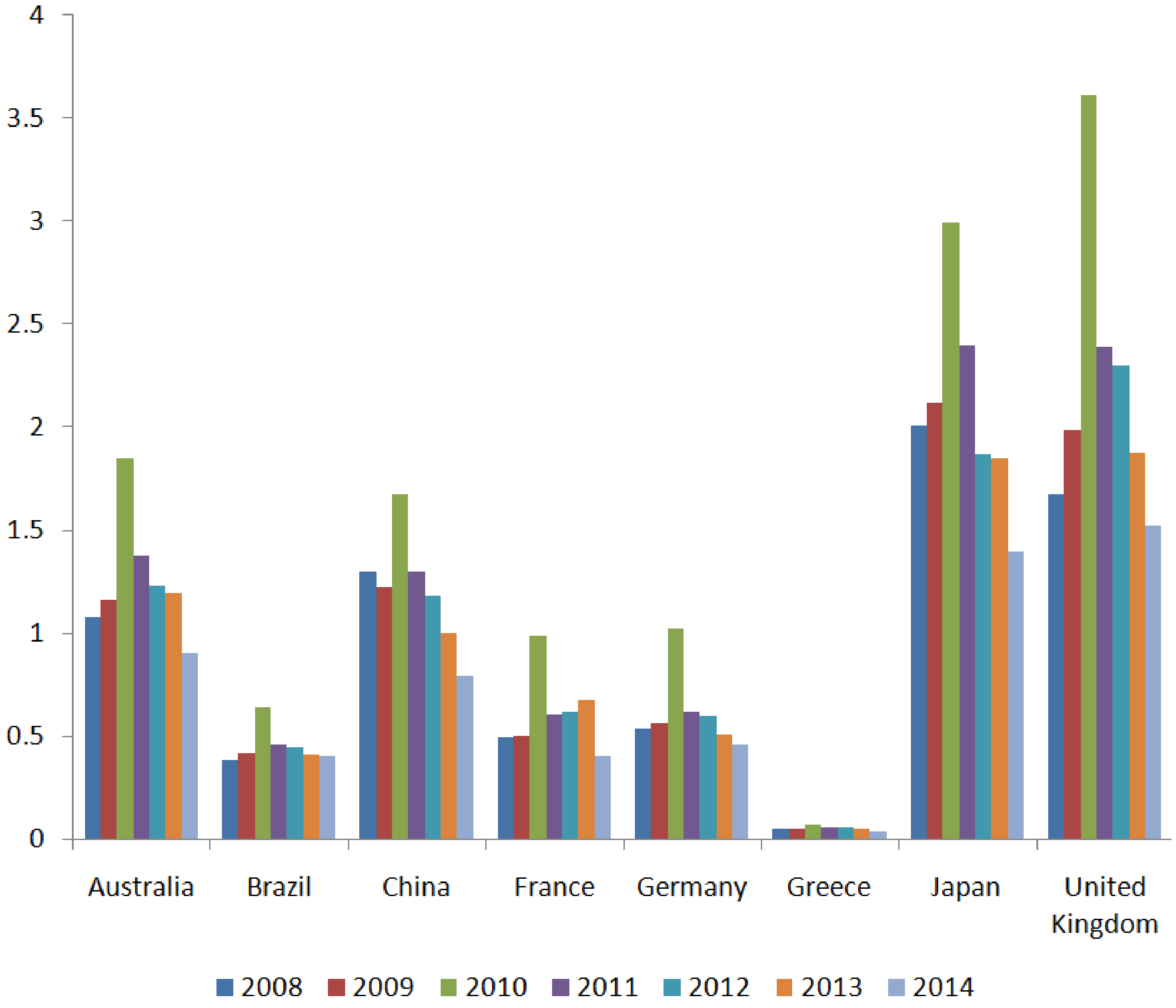
Figure 1: ADR mispricing for a select group of countries



Notes: This figure shows ADR mispricing as a percent, as estimated by the following equation:

$$ADR\ mispricing_{it} = \left|\frac{ADR\ price_{it} - Underlying\ stock\ price_{it}}{Underlying\ stock\ price_{it}}\right|.$$

Figure 2: Wikipedia country profile page views for select countries (in billions)



Notes: The country-specific investor attention measure, Wikipedia country profile page views, is obtained from the Wikipediatrends.com website. This chart shows the number of Wikipedia page views for each country by year in billions.

The dependent variable in the second-stage regression is ADR mispricing, investor attention (*Wikipedia country page views)* is the explanatory variable of interest, α is the constant, u is the residual and X is a vector of control variables. The set of control variables includes: $1/P$ is the inverse price of the underlying stock which is often used in the ADR literature as a proxy for transaction costs, dividend yield is the dividend as a percentage of the underlying stock price, and volume is the log of the ADR trading volume. Additionally, following Mollick and Assefa (2013), we include a crisis dummy variable that assumes the value of 1 between January 2008 and June 2009 and zero otherwise.[8] Market value is the log of the product of the number of outstanding shares times the current price of the underlying

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[8]The National Bureau of Economic Research (NBER) dates the crisis from December 2007 to June 2009. Since the data for this study begins on January 2008, we use that as the starting point for the dummy. More information can be found at: http://www.nber.org/cycles.html.

stock. Amihud is an "illiquidity" measure that is calculated by dividing the absolute value of an ADR return by its respective trading value: the higher value the lower liquidity, it is retrieved from Amihud (2002). Level I dummy is a binary variable that is equal to 1 for the ADRs of Level I and zero otherwise.

Table 1: Descriptive Statistics

Variables	N	Mean	Median	SD
Mispricing (%)	84,093	10.80	1.91	20.70
Investor Attention	130,788	585,921	534,750	296,012
Returns	83,798	0.08	0.04	0.50
1/P	84,673	0.31	0.07	3.07
Volume	68,753	10,683	187	50,245
Market Value	85,564	12,883	4,656	27,079
Dividend Yield (%)	85,642	3.01	2.03	5.41
Crisis	130,788	0.21	0.00	0.41

Note: This table reports the summary statistics for the variables in this study. All variables are in a monthly frequency. The time span is from January 2008 through December 2014. The variables are as follows: ADR mispricing, investor attention (Wikipedia country page views is the proxy of investor attention), volume, market value, absolute returns (|Returns|), inverse price (1/P), dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The data on ADRs is obtained from DataStream. The country-specific investor attention measure, Wikipedia page views, is obtained from the Wikipediatrends.com website.

Table 1 reports the descriptive statistics. The table shows the summary statistics of the entire sample for the variables used in this study. The mean and median values of ADR mispricing are 10.80% and 1.91%, respectively. The ADR mispricing is higher in 2008 and 2009, that is, during the Great Recession. The mean and median values of Wikipedia views are 585,921 and 534,750, respectively. The number of views grows from 2008 to 2010 and then the trend reverses until the last year of the sample. The absolute value of returns, a measure used to construct the Amihud's illiquidity measure, ($\text{Amihud} = \frac{1}{D_i}\sum_{d=1}^{D_i}\frac{|\text{ADR returns}|_{i,d}}{\text{ADR trading value}_{i,d}}$), has a mean of 0.08 and a median of 0.04. The inverse price (1/P) of the underlying stock, a proxy for transaction costs, has a mean of 0.31/$ and median of 0.07/$. The mean and median values of ADR trading volumes are 10,683 and 187, respectively. Market value has a mean of $12,883 and a median of $4,656. The dividend yield averages 3.01% with a median of 2.03%.

Table 2: Correlation Matrix

	Mispricing (%)	Investor Attention	Returns	1/P	Volume	Market Value	Dividend Yield (%)	Crisis	Level I Dummy
Mispricing	1.000								
Investor Attention	-0.0230	1.000							
Returns	0.0307	-0.0020	1.000						
1/P	0.0926	0.0060	0.0180	1.000					
Volume	-0.0907	-0.0354	-0.0231	-0.0221	1.000				
Market Value	-0.1218	0.0539	-0.0460	-0.0997	0.5298	1.000			
Dividend Yield	0.1075	-0.0611	0.0260	0.0938	0.0339	-0.0802	1.000		
Crisis	0.0696	-0.0444	0.0261	-0.0014	0.1521	-0.0121	0.0396	1.000	
Level I Dummy	0.0351	0.1227	0.0077	0.0191	-0.6226	-0.1709	-0.0325	-0.1106	1.000

Note: This table reports the correlation coefficients for the variables used in this study. The time span is from January 2008 through December 2014. The variables are as follows: ADR mispricing, investor attention (Wikipedia country page views is the proxy of investor attention), volume, market value, absolute returns, inverse price, dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The Level I Dummy is a binary variable that is equal to 1 for Level I ADRs and zero otherwise.

Table 2 reports the correlation matrix. As hypothesized, ADR mispricing is inversely related to investor attention (Wikipedia views). This correlation coefficient (-0.023) provides preliminary insight into the relationship between these two variables. ADR mispricing is also inversely related to volume, and market value, and has a positive correlation to absolute returns, inverse price, and dividend yield, all of which is in line with previous literature. Most of the correlations in the correlation matrix are relatively low, except for the correlation (0.53) between volume and market value, which indicates that more valuable firms have higher trading volumes, and the volume and the Level I dummy (-0.62), showing that Level I ADRs' trading volume is smaller than the ones from ADRs of other levels (e.g., Levels II and III).

3. Results

Table 2: 2SLS Estimation Results

Independent variables	**Dependent variable: ADR mispricing**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Investor Attention	-3.295***	-3.231***	-2.892***	-2.815***	-3.270***	-2.989***
	(0.242)	(0.242)	(0.242)	(0.234)	(0.250)	(0.247)
1/P	1.078***	1.079***		3.107***		2.973***
	(0.141)	(0.140)		(0.366)		(0.351)
Dividend Yield	1.579***	1.547***	1.646***	1.306***	1.488***	1.318***
	(0.068)	(0.067)	(0.078)	(0.064)	(0.066)	(0.064)
Volume	-0.387***	-0.425***	-0.247***			
	(0.016)	(0.016)	(0.018)			
Crisis		2.508***				2.112***
		(0.177)				(0.177)
Market Value			-0.668***	-0.740***		-0.669***
			(0.054)	(0.044)		(0.044)
Amihud				11.320***	15.290***	11.170***
				(3.754)	(4.077)	(3.682)
Level I dummy					1.625***	1.347***
					(0.117)	(0.118)
Constant	48.460***	47.490***	48.430***	46.650***	44.880***	47.000***
	(3.227)	(3.219)	(3.230)	(3.150)	(3.264)	(3.259)
Observations	52,589	52,589	52,582	51,943	51,953	51,943
Number of ADRs	1,840	1,840	1,840	1,840	1,840	1,840
F-statistic of 2SLS regression	288.88***	261.42***	253.45***	192.93***	186.7***	163.7***
P-value of instrument relevance	0.00	0.00	0.00	0.00	0.00	0.00
Hansen overidentification statistic	141.819***	157.596***	131.539***	59.328***	78.002***	99.205***
RP^2	2.2%	2.8%	2.4%	2.1%	1.0%	2.5%

*Note: This table reports estimation results of the various 2SLS instrumental variable regressions; see equations 2 and 3 in the text. The numbers in parentheses are White heteroscedasticity-consistent standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels. The variables in the study are ADR mispricing, Wikipedia views is the measure of investor attention, volume, market value, absolute returns, inverse price, dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The Level I dummy is a binary variable that is equal to 1 for Level 1 ADRs and zero otherwise.*

Tables 3 through 5 report 2SLS estimation results for 1,840 ADRs from 31 countries. The dependent variable is ADR mispricing, while Wikipedia views are the proxy for country-specific investor attention.

FIFA World Cup ranking score and UN World Heritage sites are instrumental variables in controlling potential endogeneity bias. The instrument specification tests reject both null hypotheses of weak instrument relevance and overidentification biases for all regressions in Tables 3, 4, and 5.[9]

Table 3 shows 2SLS regression results for the entire sample, with the total number of observations varying between 51,943 and 52,589. The variable, investor attention, displays a negative coefficient that ranges from -3.3 to -2.8; which means that as investor attention increases by 1 percent, we expect ADR mispricing to decrease by around 3 percent.[10] These results are similar to others found in prior literature (e.g., Eichler, 2012). Our results differ in that they include a much larger data set, which includes 1,840 ADRs and a much greater number of observations. Furthermore, our investor attention measure differs from that of Eichler's (2012). The coefficients for investor attention are economically and statistically significant at the 1% level across all six specifications. The control variables display the expected signs: inverse price (1/P), dividend yield, crisis dummy, Amihud and Level I dummy are positive and significant; volume and market value are negative and significant. It is important to mention that both the sign of the coefficient and the statistical significance confirm our hypothesis that higher country-specific attention leads to higher attention to securities from such countries, and therefore, allow less room for deviations from the price parity condition. The idea is that overall, if investors pay more attention to securities from one country, they will identify arbitrage opportunities much faster than from countries that are not on their radar.

Table 3: 2SLS Regressions by ADR Level

Independent variables	Dependent variable: ADR mispricing					
	Level I			Levels II and III		
	(1)	(2)	(3)	(4)	(5)	(6)
Investor Attention	-4.246*** (0.426)	-4.066*** (0.418)	-3.406*** (0.366)	-1.786*** (0.250)	-1.525*** (0.237)	-1.540*** (0.234)
1/P	2.178*** (0.344)		2.559*** (0.480)	3.572*** (0.564)		3.142*** (0.511)
Dividend Yield	3.062*** (0.140)	2.410*** (0.124)	1.368*** (0.090)	1.069*** (0.075)	1.062*** (0.076)	1.067*** (0.075)
Crisis	3.496*** (0.299)		2.717*** (0.246)	1.012*** (0.207)		1.040*** (0.208)
Market Value		-3.743*** (0.073)	-1.002*** (0.065)		-0.368*** (0.044)	-0.280*** (0.045)
Amihud			10.290*** (3.536)			305.900* (178.600)
Constant	60.520*** (5.650)	91.550*** (5.687)	56.720*** (4.986)	25.600*** (3.268)	26.090*** (3.239)	24.950*** (3.239)
Observations	47,841	47,742	38,828	13,228	13,228	13,115
Number of ADRs	1,322	1,322	1,322	235	235	235
F-statistic of 2SLS regression	252.88***	1052.3***	139.34***	73.51***	86.44***	56.17***
P-value of instrument relevance	0.00	0.00	0.00	0.00	0.00	0.00
Hansen validity test statistic	4.939**	124.495***	53.863***	394.323***	443.09***	400.478***
RP^2	5.6%	11.9%	2.3%	3.2%	2.8%	3.6%

[9]The first-stage estimation results, from the 2SLS model presented in Table 3, are available in Table 6 in the appendix. This table also displays the Wu-Hausman endogeneity tests statistic, Sanderson-Windmeijer (SW) first-stage chi-squared test of under-identification statistic and *F*-statistic test of weak identification of individual endogenous regressors. First-stage estimation results for the other estimations (Tables 4 and 5) are available upon request.

[10]The coefficients are interpreted this way because they are estimated using a level-log regression.

*Note: This table reports estimation results of 2SLS instrumental variable regressions by ADR level; see equations 2 and 3 in the text. The first three columns display results for Level I, while the last three columns show results for Levels II and III together. The numbers in parentheses are White heteroscedasticity-consistent standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels. The variables in the study are ADR mispricing, Wikipedia views is the measure of investor attention, volume, market value, absolute returns, inverse price, dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The Level I dummy is a binary variable that is equal to 1 for the ADRs of Level I and zero otherwise.*

Table 4 shows the 2SLS regressions by ADR levels. The first three columns correspond to Level I ADRs, with the number of observations ranging from 38,828 to 47,841. The last three columns are regressions for Level II and III ADRs, totaling about 13,200 observations. Our results show that investor attention has a stronger negative impact on ADR mispricing for Level I ADRs. The coefficients for investor attention on Level I ADR returns range from -4.246 to -3.406, versus the smaller coefficients for investor attention on Level II and III ADRs, which range from -1.786 to -1.525. Our results expand on the literature since Eichler (2012) does not examine how investor attention influences ADR mispricing by ADR level. With respect to the control variables, the inverse price (1/P) has a stronger positive effect on mispricing for Level II and III ADRs compared to Level I ADRs. The coefficient for the dividend yield is larger for Level I ADRs. The coefficient for the crisis dummy variable indicates that higher mispricing is associated with Level I ADRs. The coefficient on market value indicates a stronger negative effect on mispricing for Level I ADRs. Finally, Amihud's illiquidity coefficient suggests a higher sensitivity to changes in the degree of liquidity for Level II and III ADRs (305.9), than for Level I (10.29).

Table 5: 2SLS Regressions by Industry

Independent variables	Dependent variable: ADR mispricing									
	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care	Industrials	Oil & Gas	Tech	Telecoms	Utilities
Investor Attention	-3.235***	0.017	-4.560***	0.412	-1.970***	-6.537***	-2.544***	-9.977***	-11.500***	1.019
	-0.452	-0.518	-0.542	-0.656	-0.276	-0.91	-0.787	-1.423	-1.089	-1.055
1/P	1.901***	4.129***	15.900***	-2.530***	14.660***	-0.551	9.990***	5.300***	-7.688	7.164***
	-0.425	-0.703	-2.914	-0.958	-1.6	-3.59	-1.911	-0.966	-6.765	-2.704
Dividend Yield	-0.08	2.958***	0.455***	1.978***	0.799***	0.685***	0.242	-1.742***	0.993***	-0.620***
	-0.193	-0.225	-0.152	-0.184	-0.094	-0.214	-0.249	-0.223	-0.239	-0.141
Volume	-0.803***	-0.373***	-0.928***	-0.478***	-0.429***	-0.114*	-0.048	-0.621***	0.354***	0.167***
	-0.065	-0.038	-0.088	-0.056	-0.034	-0.059	-0.084	-0.055	-0.119	-0.063
Crisis	3.664***	3.152***	1.094***	4.552***	0.529***	1.770***	-0.273	0.888***	1.292*	1.423**
	-0.516	-0.408	-0.392	-0.54	-0.172	-0.49	-0.467	-0.272	-0.716	-0.557
Amihud	6.575	12.96	35.470***	11.73	19.410*	16.250**	-2.93	31.920*	263.400**	58.700***
	-7.128	-7.9	-13	-8.319	-10.14	-6.697	-2.182	-18.95	-114.7	-15.44
Level I dummy	-1.343***	0.995***	-2.007***	-3.480***	-1.950***	-0.247	3.468***	0.662**	1.379*	2.627***
	-0.361	-0.231	-0.293	-0.411	-0.195	-0.675	-0.552	-0.327	-0.726	-0.548
Constant	51.320***	1.265	68.510***	2.559	29.740***	91.070***	36.240***	137.600***	150.400***	-11.02
	-6.384	-6.722	-7.577	-8.345	-3.688	-11.82	-10.9	-18.9	-14.01	-13.63
Observations	5,766	8,279	5,019	8,168	2,579	9,313	2,804	2,597	2,704	3,251
Number of ADRs	173	211	161	225	119	303	89	80	51	77
F-statistic of regression	50.44***	64.11***	28.57***	46.78***	44.14***	18.66***	43.35***	38.88***	19.49***	12.40***
IV relevance (*p*-value)	0	0	0	0	0	0	0	0	0	0
Hansen overid. statistic	7.629***	80.375***	15.235***	18.648***	0.859	97.527***	67.308***	0.876	99.569***	0.508
R^2	3.20%	10.80%	8.60%	4.80%	15.80%	2.50%	9.00%	5.40%	9.70%	0.03%

*Notes: This table reports estimation results of 2SLS instrumental variable regressions by industry; see equations 2 and 3 in the text. The numbers in parentheses are White heteroscedasticity-consistent standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels. The variables in the study are ADR mispricing, Wikipedia views is the measure of investor attention, volume, market value, absolute returns, inverse price, dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The Level I dummy is a binary variable that is equal to 1 for the ADRs of Level I and zero otherwise.*

Table 5 displays 2SLS regressions by industry. We find that investor attention (Wikipedia page views) has a negative and significant impact on ADR mispricing for most industries. Investor attention has the greatest impact on the following industries: telecommunications (-11.50), technology (-9.98), industrials (-6.54), consumer services (-4.56), basic materials (-3.235), oil and gas (-2.54), and health care (-2.38). Statistical insignificance of investor attention for consumer goods, financials, and utilities may indicate that these industries are less sensitive to the marginal impact of investor attention. In fact, the lack of significance for utilities and financials are consistent with the corporate finance literature, which often excludes those industries due to the former's regulated nature and the latter's spotty historical coverage of firms (e.g., Fama and French 2001). For the control variables, the results are in line with our previous findings in Table 4. This set of results also contributes to the literature, given that Eichler (2012) does not focus on how investor attention influences ADR mispricing by industry.

4. Conclusion

There is a growing body of literature on ADR mispricing, but the focus of more recent studies has been on behavioral finance to try to explain this deviation from the law of one price (Grossmann et al., 2007; Hwang, 2011; Wu et al., 2017). Moreover, recent studies have shown that investor attention plays a role in the portfolio selection process (Barber & Odean, 2008; Van Nieuwerburgh & Veldkamp, 2010). Only one prior study has examined the link between investor attention and ADR mispricing (Eichler, 2012). Our study expands on Eichler (2012).

This paper contributes to the literature on the influence of investor attention on ADR mispricing in the following distinct ways. First, we use a unique measure of investor attention, Wikipedia country-profile page views. To the best of our knowledge, this is the first study that tests the impact of Wikipedia country page views (a proxy for investor's attention) on ADR mispricing. Second, we expand the dataset of ADRs to include a larger sample size that spans from 2008 to 2014, with a larger number of observations. Our sample period allows us to examine if the Great Recession had an influence on the relationship between investor attention and ADR mispricing. Furthermore, we include Level I ADRs, whereas prior studies only included Level II and Level III ADRs (Eicher, 2012). Adding Level I ADRs allows us to examine if investor attention has a larger effect on mispricing compared to Level II and Level III ADRs. Finally, we examine the role of investor attention across ADR industries.

The results from the 2SLS models show that country-specific investor attention has an inverse relationship to ADR mispricing. Overall, high Wikipedia country-profile page views are related to lower ADR mispricing for a sample of 1,840 cross-listed securities from 31 countries. That is, as investors pay more attention to a country, the level of ADR mispricing is reduced significantly. Furthermore, when we *disaggregate* ADRs by level (i.e., I versus Level II and III), our results show that investor attention's influence on ADR mispricing depends on the ADR level. For instance, we show that Wikipedia page views have a greater influence on level I ADRs compared to levels II and III ADRs (the coefficients on Level I are much larger than those of levels II and III). These results confirm the previous findings of Eichler (2012) and are consistent with the previous literature (Beckmann et al., 2015); the ADR level determines the degree of ADR mispricing. Additionally, our results show that the Great Recession also significantly impacts how investor attention influences ADR mispricing. For instance, the crisis dummy variable is larger for level I ADRs than for levels II and III, which means that during times of turmoil, this effect was increased. A possible reason for this increased effect could also be related to the fact that Level I ADRs are less regulated and riskier overall. Therefore, during recessionary periods, investors prefer to invest in bigger companies with longer track records rather than smaller foreign firms, magnifying the effect of the mispricing. Our study also shows that investor attention influences ADR mispricing across industries. For example, higher levels of investor attention reduced ADR mispricing for the consumer services industry. However, not all industries were influenced by investor attention (e.g., consumer goods, financials, and utilities). Perhaps the steady cash flow nature of the utility sector and its relevant public interest, along with the overall increased regulatory oversight in the financial industry, could have an impact in the price discovery process altogether for these industries, making the investor attention measure less relevant or at least the coefficients insignificant in our study. Lastly, all the tests for correctly specified models, such as overestimation, under-identification, and weak under-identification, provide robustness to the empirical results. Overall, this study sheds new light on how investor attention influences ADR mispricing.

The economic implications of this study are quite important for practitioners. Considering that an investor could develop a plan to observe ADRs from less popular countries to find arbitrage opportunities using long and short positions depending on whether the ADR is sold at a premium or at a discount.

This study is not without its limitations. First, country population, gross domestic product (GDP), and educational level could be used as control variables for country popularity proxied by the Wikipedia profile page views. For instance, a country's population could drive the number of visits a given profile receives on a periodical basis. Second, a more educated country could also draw more attention from its citizens or foreigners, thus driving up the level of attention it receives. Lastly, when data becomes available, the country popularity measure could be retrieved in other languages to contrast the results from the English country profiles since ADRs are not restricted to U.S. investors only. Finally, other variables, such as financial regulation, could pose a limit to arbitrage, as proposed by some literature. However, that is to be explored in a future research project, as well as the proxy for attention and the sign of mispricing (premium or discount).

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Appendix 1: First Stage Estimation Results

Independent variables	**Dependent variable: Investor Attention**					
	-1	**-2**	**-3**	**-4**	**-5**	**-6**
UN World Heritage Sites	0.017***	0.017***	0.016***	0.016***	0.016***	0.016***
	0	0	0	0	0	0
FIFA Ranking	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	0	0	0	0	0	0
1/P	0.003	0.003		0.045***		0.361***
	-0.002	-0.002		-0.011		-0.011
Dividend Yield	-0.020***	-0.020***	-0.017***	-0.020***	-0.018***	-0.016***
	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
Volume	-0.002***	-0.001**	-0.006***			
	-0.001	-0.001	-0.001			
Crisis		-0.039***				-0.028***
		-0.005				-0.005
Market Value			0.020***	0.012***		0.018***
			-0.002	-0.001		-0.001
Amihud				-0.055	-0.103***	-0.073**
				-0.036	-0.035	-0.036
Level I dummy					-0.104***	0.110***
					-0.004	-0.004
Constant	12.830***	12.830***	12.670***	12.700***	12.740***	12.580***
	-0.005	-0.005	-0.013	-0.013	-0.005	-0.14
Observations	52,589	52,589	52,582	51,943	51,953	51,943
Wu-Hausman *F*-test	129.117***	130.28***	104.20***	108.84***	118.35***	110.31***
Sanderson-Windmeijer Under-identification Chi-sq	13,062***	13,043***	12,721***	12,991***	12,453***	12,234***
Sanderson-Windmeijer Weak identification F-test	6,530.63***	6,521.10***	6,360.13***	6,495.07***	6,225.91***	6,115.96***
Number of ADRs	1,840	1,840	1,840	1,840	1,840	1,840
*RP*²	20.20%	20.30%	20.50%	20.40%	21.20%	21.50%

*Note: This table reports estimation results of the first stage regressions of the instruments on the variable of interest. We assume Wikipedia page views as the endogenous variable, while the number of United Nations World Heritage sites and the FIFA World Cup ranking score are used as instruments. The numbers in parentheses are White heteroscedasticity-consistent standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels. The Wu Hausman F-test report the test statistics, the H0 is that the regressor is exogenous. The Sanderson-Windmeijer are first stage chi-squared and F statistics tests of under- identification and weak identification of individual endogenous regressors. The variables in the study are ADR mispricing, Wikipedia views is the measure of investor attention, volume, market value, absolute returns, inverse price, dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The Level I dummy is a binary variable that is equal to 1 for the ADRs of Level I and zero otherwise.*

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FUTURES PRICES LINKAGES IN THE US SOYBEAN COMPLEX

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Abstract

This work investigates the linkages among the futures prices of soybeans, soybean meal, and soybean oil in the US. This has been pursued using a flexible methodology that allows modelling price relationships at different parts of their joint distribution. According to the empirical results, the markets are strongly connected in the vertical direction regardless of the sign and the size of shocks. The meal and oil prices maintain a negative relationship at the median and the upper quantiles**,** but they are not connected under large negative shocks. The soybean market is a net transmitter of price risk to the other two markets, while price shocks around the median tend to be transmitted with higher intensity relative to those at the extremes.

JEL: G14, C12

Keywords: US, Soybean Complex, Futures Prices, Risk Transmission, Asymmetry

1. Introduction

Soybean is the second largest row crop in the US. It is processed ("crushed") in two joint products: soybean meal and soybean oil. Soybean meal is predominantly used as a protein source in livestock feed ratios. Soybean oil has been traditionally used for human consumption (cooking oil, salad dressings, etc.). In recent years, however, an increasing part of it has been utilised as an input in biodiesel production[1].

The futures markets for soybeans and its products in the US are among the oldest and the most liquid ones. The linkages among the futures prices of soybean, meal, and oil are important for farmers, processors, soybean meal and oil users, futures markets participants, and policymakers. Farmers typically enter the futures markets to hedge their exposure to soybeans' price risk. Processors are primarily interested in establishing a floor for their "crush spread" (the difference between the combined value of meal and oil and the value of soybeans used to produce them). To this end, they typically long (sell) the crush spread by buying soybean futures contracts and selling meal and oil contracts. Speculators may long or short (sell) the crush spread, depending on whether they expect

[1] Brazil (with 36 %) is the biggest producer of soybeans, followed by the US (29%), Argentina (16%), and China (5%); China (with 29%) is the biggest producer of soybean meal, followed by the US (19%), Brazil (17%), and Argentina (11%); China (with 27%) is the biggest producer of soybean oil followed by the US (20%), Brazil (17%), and Argentina (11%). The top exporter of soybeans is Brazil and the top importer is China; the top exporter of soybean meal is Argentina and the top importer is the EU-28; the top exporter of soybean oil is again Argentina and the top importers are India and China (https://www.fao.org/statistics/en/)"

it to get wider or narrower in the future[2]. Policymakers are mainly concerned with the well-functioning of markets and the viability of the relevant industries.

The US soybean complex potentially presents a special interest for research economists since it involves price relationships in two directions: the vertical (between soybeans and its products) and the horizontal (between meal and oil). The type (positive or negative), the intensity (strong or weak), and the mode (symmetric or asymmetric) of these linkages contain useful information for assessing the well-functioning of the network of the three interrelated markets and for designing appropriate risk management strategies (e.g., Mayer and von Cramon Taubadel, 2004; Reboredo, 2012, Hautsch *et al.*, 2015). As noted by Collins (2000), profits of firms with multiple commodity endowments (such as the soybean processing ones) are to some degree "self-hedged" provided that input and output prices are positively correlated and hedging one commodity in isolation may actually increase the overall level of risk. It is surprising, therefore, that the number of empirical works on the topic is quite small.

Rausser and Carter (1983), assessed the efficiency of futures markets in the US soybean complex using a structurally based Autorergessive Integrated Moving Average (ARIMA) model. They obtained some evidence of inefficiency for the soybean and soybean meal markets but not for the soybean oil market. Beutler and Brorsen (1985) investigated the lag-lead relationships among daily spot (cash) prices of soybeans, meal, and oil using a 3-variate VAR model. They found that the input price led to the products' prices and that past oil prices had a negative effect on meal prices. Collins (2000) compared alternative strategies for minimising the day-to-day variability of the crush spread. According to his results, multivariate or univariate risk-minimizing models offered no risk-management advantages over a simple equal and opposite hedge[3]. Babula *et al.* (2004), using cash prices, multivariate VAR models, Directed Acyclical Graphs, and Forecast Error Variance Decompositions (FEVD), reported bi-directional causality between soybeans and meal and uni-directional causality from soybeans to oil. Adrangi *et al.* (2006), using futures prices and bi-variate VECM models ((soybeans, meal) and (soybeans, oil)) found that each pair of prices was cointegrated and that the prices of meal and oil were weakly exogenous. Finally, Simanjuntak *et al.* (2020), using Rotterdam soybean prices, Hamburg meal prices, and Dutch oil prices, and a 3-variate VECM model found one cointegrating vector and that the price of soybean bears the burden of convergence to the long-run equilibrium.

A common characteristic of the above-mentioned empirical works is that they investigated price relationships in the soybean complex "on average" (i.e., around the mean of their joint distribution). However, there is no *a priori* reason to assume that the pattern of linkages is the same under different signs and sizes of shocks. Quite the contrary. There is plenty of empirical evidence that the type, intensity, and mode of a relationship among stochastic processes may be quantile-dependent (e.g., Barunik and Kley, 2019; Ando *et al.*, 2022).

The present work revisits futures prices linkages in the US soybean complex. In doing so, it departs from the existing literature in two important ways. First, it relies on a flexible methodology, proposed by Hautsch *et al.* (2015), that allows modelling relations at different parts of the 3-variate (joint) price distribution and in two directions (vertical and horizontal)[4]. Second, it employs a barrage of statistical tests to identify and quantify asymmetric linkages with respect to the sign, size, and origin (a particular market in the complex) of price shocks. Quantile-dependent and asymmetric price relationships are important for risk management in the soybean complex because hedging strategies that may be suitable for one part of the joint price distribution (i.e. for a given state of markets) may be unsuitable for another part of it. For example, if prices do not move in the same direction at certain quantiles,

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[2] https://www.cmegroup.com/education/files/soybean-crush-reference-guide.pdf.

[3] That type of hedge involves taking equal and opposite positions in the spot (cash) and futures markets (so that gain (loss) in one market is offset by loss (gain) in the other market and the hedger's risk exposure is reduced or eliminated).

[4] Among the recent applications of the approach by Hautsch *et al.* (2015) are the works of Ngugen *et al.* (2020) on cryptocurrencies, Fousekis and Grigoridis (2022) on international coffee markets, and Fousekis (2022) on the EU olive oil markets.

profit is no longer “self-hedged”; strategies, therefore, that are based on the information about price co-movement “on average” may actually increase risk. Earlier empirical studies on the linkages between soybeans, soybean meal, and soybean oil prices have failed to consider this possibility. Section 2 presents the analytical framework, and Section 3 the data, the empirical models and the empirical results. Section 4 offers conclusions and suggestions for future research.

2. Analytical Framework

Let r_t^i be a stationary stochastic process (here, the price-log return of given Commodity *i*) at *t*= 1, 2, …, *T*. The *lower-tail value-at-risk* ($VaR_{q,t}^{i,L}$) is the *q*th quantile of the unconditional distribution of r_t^i (with $q \in (0,0.5)$); it gives the maximum value r_t^i will attain with confidence level 1-*q*. Let now r_t^j be another stationary stochastic process. The *lower-tail conditional value-at-risk* ($CoVaR_{q,t}^{i/j,L}$) is the *q*th quantile of the conditional distribution of r_t^i; it gives the maximum value r_t^i will attain with confidence level 1-*q*, provided that $r_t^j \le VaR_{q,t}^{j,L}$. (e.g., Adrian & Brunnermeier, 2011; Borri, 2019). The *upper-tail conditional value-at-risk* ($CoVaR_{q,t}^{i/j,U}$) is defined analogously; it is the (1-*q*)th of the conditional distribution of r_t^i; it gives the minimum value r_t^i will attain with confidence level 1-*q*, provided that $r_t^j \ge VaR_{1-q,t}^{j,U}$.

The notions of conditional lower- and upper-tail value-at-risk can be easily extended to multiple conditioning stochastic processes. For a *n*x1 vector of stationary stochastic processes the *q*th quantile of the conditional distribution of r_t^i is

$$q = prob\left(r_t^i \le \frac{VaR_{q,t}^{i,L}}{r_t^1} \le VaR_{q,t}^{1,L}, r_t^2 \le VaR_{q,t}^{2,L}, \dots, r_t^n \le VaR_{q,t}^{n,L} \right) \tag{1}$$

while the (1-*q*)th quantile of it is

$$q = prob\left(r_t^i \ge \frac{VaR_{1-q,t}^{i,U}}{r_t^1} \ge VaR_{1-q,t}^{1,U}, r_t^2 \ge VaR_{1-q,t}^{2,U}, \dots, r_t^n \ge VaR_{1-q,t}^{n,U} \right) \tag{2}$$

The standard quantile regression (Koenker and Bassett, 1978) offers an efficient way to implement empirically a *CoVaR* model. For the lower-tail *CoVaR*, Hautsch *et al.* (2015) and Ngueyen *et al.* (2020) proposed the estimation of

$$VaR_{q,t}^{i,L} = a_q^{i,L} + \sum_{j=1, j\neq i}^{n-1} \beta_q^{i/j,L} E_{q,t}^{j,L} + \sum_{k=1}^{K} \gamma_q^{i/k} Z_{q,t}^k + u_{q,t}^{i,L} \tag{3}$$

where $E_{q,t}^{j,L}$ is the *loss exceedance* for r_t^j (a variable defined as $E_{q,t}^{j,L} = r_t^j$ for $r_t^j \leq VaR_{q,t}^{j,L}$ and $E_{q,t}^{j,L} = 0$ otherwise), Z_k are other relevant variables, and $u_{t,q}^{iL}$ is the error term. The coefficient $b_q^{i/j,L}$ in (3) represents the sensitivity of r_t^i to negative shocks in r_t^j. $b_q^{i/j,L} > 0$ implies that values of $r_t^{j,L}$ below $VaR_{q,t}^{j,L}$ increase the probability of observing values of r_t^i below $VaR_{q,t}^{i,L}$; $b_q^{i/j,L} = 0$ suggests that there is no price-risk transmission from commodity *j* to *i*, at the *q*th quantile; finally, $b_q^{i/j,L} < 0$ implies that values of $r_t^{j,L}$ below $VaR_{q,t}^{j,L}$ decrease the probability of observing values of r_t^i below $VaR_{q,t}^{i,L}$ (in the latter case, therefore, extreme negative price shocks to commodity *j* may result into weak negative or even positive returns for *i*). For the upper-tail *CoVaR*, the interpretation of the model coefficients is analogous (i.e., a zero coefficient suggests no sensitivity of *i* to positive shocks to *j* whereas a positive (negative) sign implies that a positive shock to *j* increases (decreases) the probability of observing values of *i* above $VaR_{1-q,t}^{i,U}$).

The regression coefficients at quantile thresholds *q* and 1-*q* allow one to test a number of alternative hypotheses about the structure of price linkages. The sign and the statistical significance of $b_q^{i/j,L} - b_{1-q}^{i/j,U}$ provides information on the relative intensity of the transmission of price shocks at symmetric lower- and upper-quantiles (e.g., a positive and statistically significant difference will imply that shocks to *j* at the *q*th quantile are transmitted to *i* with higher intensity relative those at the (1-*q*)th quantile, while a zero difference will point to symmetric transmission with respect to the sign and the size of price shocks). The sign and the statistical significance of $b_q^{i/j,L} - b_q^{j/i,L}$ (or equivalently that of $b_{1-q}^{i/j,U} - b_{1-q}^{j/i,U}$) provides information on asymmetry with respect to the origin of shocks; that means, information on which of the two commodities is likely to be net-transmitter of price risk (e.g., Barunik *et al*., 2016; Nguyen *et al*., 2020; Fousekis & Grigoriadis, 2022).

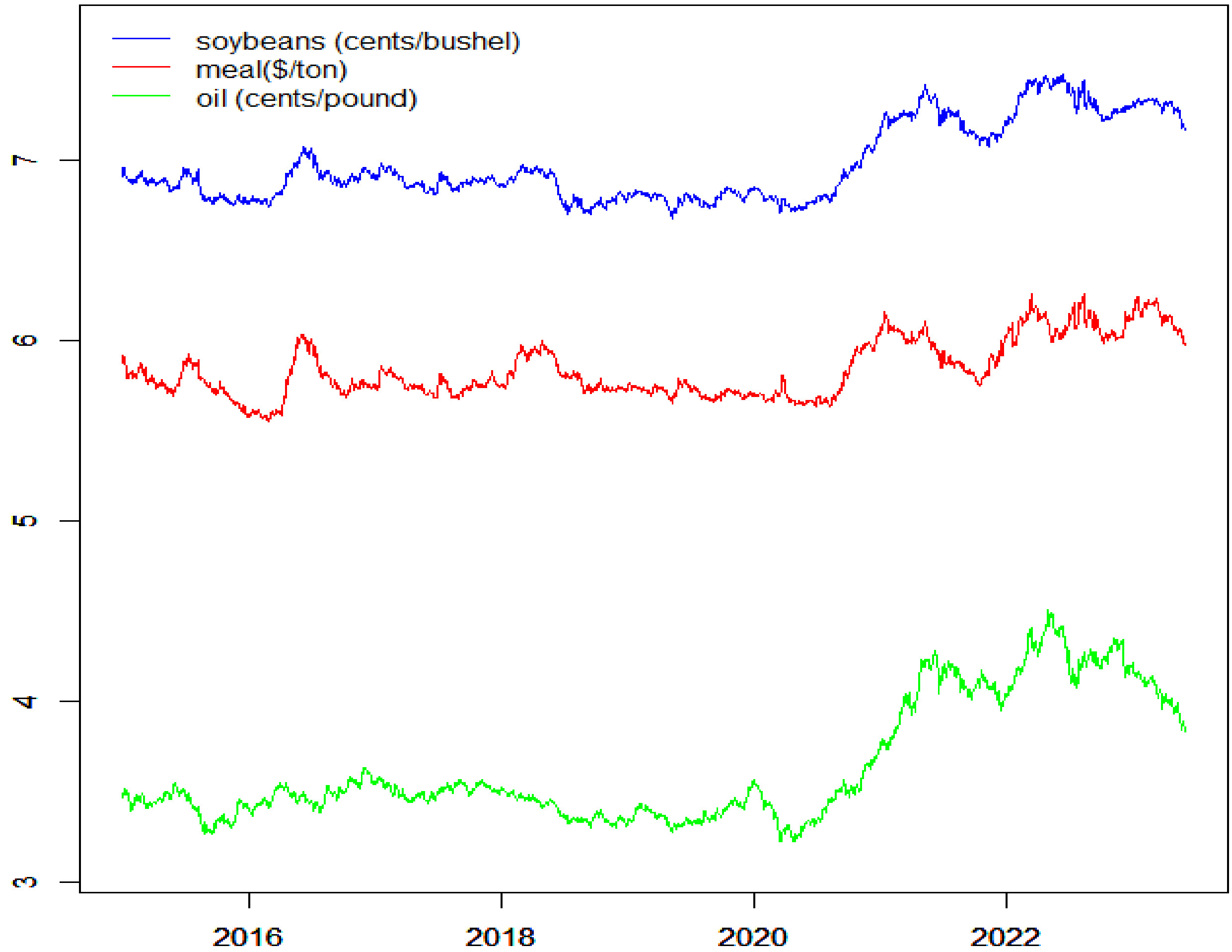
3. Data, Empirical Models, and Results

31. Data

The data for the empirical analysis are closing front-month daily prices of soybeans (in cents/bushel), soybean meal (in $/short ton), and soybean oil (in cents/pound). They were obtained from Yahoo Finance, and they refer to the period 1/1/2015 to 5/31/2023[5]. Figure 1 presents the evolution of (logarithmic) futures prices over the sample period.

[5] Price information for earlier periods is available. The sample size here has been restricted to recent periods to capture the effect of the dramatic increase in the use of soybean as an input in biodiesel production. According to the ERS-USDA, the part of domestically consumed oil directed to biodiesel production was rather small prior to 2010 but it rose from 26.4 % in 2015 to 42.9% in 2022 (https://www.ers.usda.gov/data-products/oil-crops-yearbook/). The number of observations (2115) is more than sufficient for a robust statistical analysis while empirical results based on recent information are far more relevant for policy analysis and risk-management purposes. Each Chicago Board of Trade (CBOT) soybean contract consists of 5000 bushels (or 136.1 metric tons); the soybean meal and soybean oil contracts consist of 10 metric tons each. Over the sample period, the average values of contracts traded (i.e., the volume) were 76540, 31310 and 33813 per day for soybeans, meal, and oil respectively. Traded volume in all cases has exhibited a positive (although rather weak) trend. The average values of open interest, during 2019-23, were 750000, 430000, and 400000 per day for soybeans, soybean meal, and soybean oil, respectively.

Figure 1: The evolution of (logarithmic) futures prices

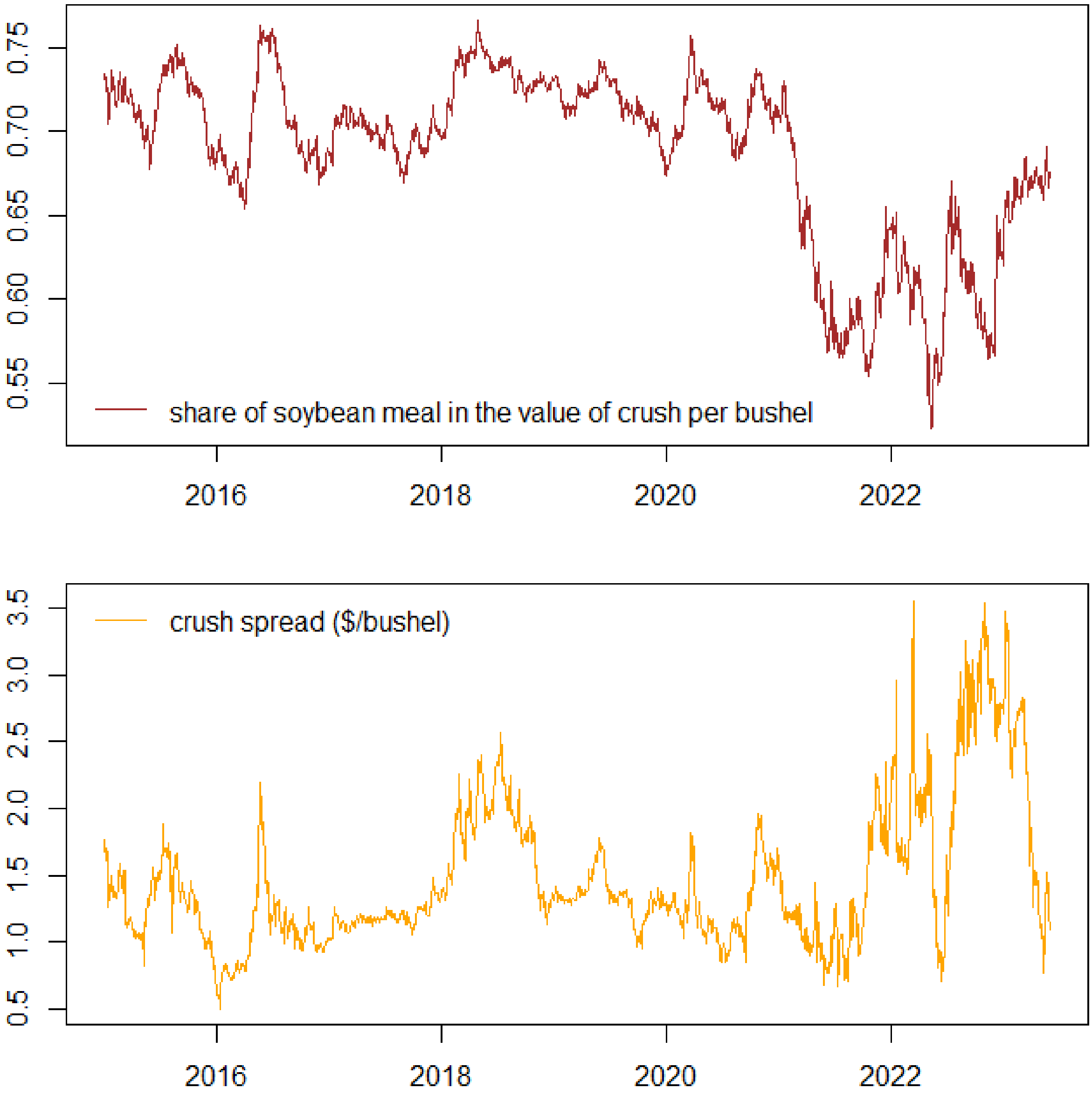


The three series followed similar trends until the first months of 2020. Since then, the price of oil has risen by about 57% of soybeans by 42%, and soybean meal by about 35 %.

Processing soybeans typically results in 80% meal and 18% oil (the exact proportions depend on soybean characteristics and the processing technology utilised). Historically, soybean meal had been the dominant source of demand for soybeans. The emergence of the biodiesel industry combined with the decline in soybean oil for domestic food use and the relatively stable demand for animal feed has induced processors to switch from "crushing for meal" to "crushing for oil" (Wisner, 2015; Gerdts, 2022). These developments have led to a sharp decline in the share of meal in the value of soybean crush, especially in the last three years (Figure 2, top). The crush spread showed considerable volatility about its mean value (1.5$ per bushel), especially since the late-2021 (Figure 2, bottom). All prices (in natural logs) are non-stationary at any reasonable level of significance; their, log-returns, however, are (weakly) stationary[6]. Therefore, the subsequent analysis here relies on log-returns.

[6] The properties of the log-levels and the log-returns have been verified through the KPSS tests. The results are available upon request.

Figure 2: The evolution of the share of meal in the value of crush (top) and the crush spread (bottom) per bushel of soybeans



Note: Author's calculations based on the relevant CME Group Guide.

3.2 Empirical Models and Results

Table 1 reports unconditional and conditional Pearson's contemporaneous correlation coefficients for the three pairs of log-returns; the unconditional range from 0.13 for meal and oil to 0.75 for soybeans and meal. Partial (conditional) correlation coefficients quantify the linear association between two stochastic processes when conditioned for one or more confounding variables, avoiding, thus, spurious correlation. The conditional correlations (calculated as suggested by Kim (2015) for soybeans and meal and soybeans and oil are higher than the corresponding unconditional ones while that for meal and oil is negative. Moreover, the differences are statistically significant. It is obvious that bi-variate modelling (as in Adrangi *et al.* (2006)) is not suitable for investigating the price linkages in the US soybean complex. The negative sign for the pair meal and oil makes perfect sense if one takes into account that meal and oil are produced jointly in (almost) fixed proportions. As the demand for oil rises (in recent years, this is precisely the case with the rapid growth in the biodiesel industry), more soybeans are crushed, increasing the supply of both meal and oil. When the demand for meal is stagnant or rises at a slower pace relative to that for oil, the “crushing for oil” will exercise downward pressure on meal prices. Gerdts (2022) argued that the relationship between oil and meal prices may be negative without, however, offering any empirical evidence of it. Adrangi *et al*. (2006) did not investigate the association between meal and oil prices; Simanjuntak *et al*. (2020) reported a single cointegrating vector in which the price of soybeans depended positively on the prices of the two joint products while the FEVD (as in Babula *et al*., 2004) does not provide any information on whether a relationship is positive or negative. The study by Beutler and Brorsen (1985) is the only one that found a negative (although a lag-lead one) impact of soybean oil prices on meal prices.

Table 1: Unconditional and Conditional Pearson Contemporaneous Correlation Coefficients Between Log-Returns

Index pair	Unconditional (1)	Conditional (2)	Difference =(2)-(1)
(Soybeans, Soybean Meal)	0.745	0.812	0.068
(Soybeans, Soybean Oil)	0.555	0.687	0.132
(Soybean Meal, Soybean Oil)	0.135	-0.501	-0.637

Note: All estimates in Table 1 are statistically significant at the 1 per cent level or less (a result obtained using bootstrap with 1000 replications).

The number of possible quantile thresholds for estimating model (3) (and the corresponding for the upper-tail CoVAR) is infinite. Following earlier studies on the topic (e.g., Nguyen *et al*., 2020; Fousekis & Grigoriadis, 2022), the present work focuses on a small number of them and, in particular, on the 5% lower, the median, and the 5% upper. The *CoVaR* model for each price return and each quantile threshold includes as control variables the corresponding exceedance levels of the other two price returns and (to account for possible autocorrelation) lags of the dependent variable[7].

The empirical analysis involves a number of single and joint coefficient tests. These have been conducted using a Wald-type statistic

$$W = (R\hat{C})'(R\hat{V}_C R')^{-1}(R\hat{C}) \quad (4)$$

where R is the restrictions' matrix, C is the parameters' vector, and $\hat{V}_C$ is the bootstrap estimate of their variance-covariance matrix (Patton, 2013). Under a null, Ω follows the χ^2 distribution with degrees of freedom equal to the number of restrictions.

Table 2 shows the sensitivity coefficients at the three quantile thresholds. At the lower 5% tail, the impact of changes in soybean prices on both meal and oil prices is positive and strongly statistically significant, and the same is true for the impact of changes in the prices of meal and oil on soybean prices. Therefore, there is plenty of evidence that the price pairs (soybeans, meal) and (soybeans, oil) tend to crush together. The two sensitivity coefficients for the pair (meal, oil), although positive, are not significant at any reasonable level. A non-zero sensitivity coefficient, points to the presence of information flow between markets and is an indication of market integration (Mayer and von Cramon Taubadel, 2004; Reboredo, 2011). From the results in Table 2, one may conclude that, at the 5 % lower tail, there is information flow both upstream and downstream and that the market pairs (soybean,

[7] For each quantile regression, the optimal lag length has been determined using the conservative Schwartz Criterion. The empirical models have been estimated using the routine *dynrq* (Package “quantreg” in R; Koenker, 2023).

meal) and (soybean, oil) are integrated. At the median and at the 5% upper tail the sensitivity coefficients for the pairs (soybeans, meal) and (soybeans, oil) are also positive and strongly statistically significant; the sensitivity coefficients, however, for the pair (meal, oil) are all negative and statistically significant at the 2.5% level (or less). The absence of a link between meal and oil at the lower tail and the negative links at the median and the upper tail may complicate, ceteris paribus, crush hedging behind which lies the idea that prices of the two joint products will move up and down together and it may create opportunities for speculators to profit from "beating" the market.

Table 2: Sensitivity coefficients

Pairs	5% Lower-tail	Median	5% Upper-tail
(Soybeans® Meal)	1.074 (<0.01)	1.455 (<0.01)	0.953 (<0.01)
(Soybeans® Oil)	1.449 (<0.01)	1.638 (<0.01)	1.027 (<0.01)
(Meal® Oil)	0.026 (0.928)	-0.881 (<0.01)	-0.360 (<0.01)
(Meal® Soybeans)	0.680 (<0.01)	0.815 (<0.01)	0.658 (<0.01)
(Oil® Soybeans)	0.524 (<0.01)	0.516 (<0.01)	0.355 (<0.01)
(Oil® Meal)	0.073 (0.760)	-0.473 (<0.01)	-0.146 (-0.025)

Note: p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 3 shows tests on the equality of the sensitivity coefficients at the three selected quantile thresholds. In all cases, the null hypothesis of symmetry has been strongly rejected suggesting that sign and the size of price shocks do matter for the pattern of information transmission from one market to the other. To shed more light on this important issue, Table 4 presents tests on the equality of sensitivity coefficients at the upper and the lower tails only. The null has been rejected only for oil and soybeans (when the price shock originates from oil). The positive sign of the test statistic in this case suggests that lower- tail shocks are transmitted with higher intensity relative to upper- tail ones. Taken together, Tables 3 and 4, imply that transmission asymmetries with respect to the sign and the size of shocks are more likely to occur between the median and the tails than between the tails of the joint distribution.

Table 3: Three-Coefficient Symmetry Tests with Respect to the Sign and the Size of Price Shocks

(Ho: The sensitivity coefficients are equal at the 5% lower, the median, and the 5% upper quantiles)

Pairs	Empirical values
(Soybeans® Meal)	-0.381 and 0.503 (<0.01)
(Soybeans® Oil)	-0.189 and 0.610 (<0.01)
(Meal® Oil)	0.907 and -0.21 (<0.01)
(Meal® Soybeans)	-0.135 and 0.157 (0.032)
(Oil® Soybeans)	0.009 and 0.161 (0.304)
(Oil® Meal)	0.547 and -0.327 (<0.01)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the median and coefficient at the median minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 4: Two-Coefficient Symmetry Tests with Respect to the Sign and the Size of Price Shocks

(Ho: The sensitivity coefficients are equal at the 5% lower, the median, and the 5% upper quantiles)

Pairs	Empirical value
(Soybeans® Meal)	0.121 (0.459)
(Soybeans® Oil)	0.421 (0.127)
(Meal® Oil)	0.386 (0.209)
(Meal® Soybeans)	0.021 (0.845)
(Oil® Soybeans)	0.169 (0.016)
(Oil® Meal)	0.219 (0.372)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

Table 5 presents symmetry tests with respect to the origin of price shocks. For all quantile levels considered, soybeans have been a net transmitter of price risk to meal and oil. Therefore, although (on the basis of Table 2) there is statistically significant information transmission upstream as well as downstream, the intensity at which information is transmitted is likely to be higher from the input to the final products' markets than the other way round. The derived demand theory (Marshall, 1920) predicts the opposite (that means, prices are first established at the final product markets, and they are transmitted subsequently upstream to the intermediate good markets). According to Adrangi *et al*. (2006), a pattern of information flow contrary to the predictions of derived demand theory may arise when the market structure changes along a continuum of vertically interrelated markets. For the US soybean complex, in particular, soybean processing is populated by several major operators (among them are Archer Daniels Midland Co, Bungle Limited, and Cargil Incorporated). As such, soybean processing may be thought of as oligopolistic/oligopolistic. Downstream, wholesaling and retailing tend to be more competitive.

Table 5: Symmetry Tests with Respect to the Origin of Price Shocks

(Ho: The origin of price shocks does not matter for the intensity of transmission)

Differences	5% lower Empirical value	Median Empirical value	5% upper Empirical value
(Meal® Soybeans) - (Soybeans® Meal)	-0.393 (0.078)	-0.640 (<0.01)	-0.294 (0.035)
Oil® Soybeans) - (Soybeans® Oil)	-0.924 (<0.01)	-1.121 (<0.01)	-0.627 (<0.01)
(Meal® Oil) - (Oil® Meal)	-0.046 (0.820)	-0.408 (<0.01)	-0.214 (0.078)

Note: (a) The empirical values are coefficient at the 5% lower-tail minus coefficient at the 5% upper-tail. (b) p-values in parentheses; obtained using bootstrap with 1000 replications.

In any case, vertical asymmetric transmission has important implications for the behaviour of the crush spread. An increase in soybeans price by 1% is likely to increase the final product's price (at the 5%

lower and the median quantile thresholds) by more than 1% working, towards widening the spread[8]. Exactly the same (i.e., widening of the spread), however, will be the case (at all quantile thresholds, again) when the prices of oil and meal increase by 1%. Therefore, soybean processors appear to have an advantage both downstream (over wholesalers and retailers) and upstream (over farmers). For the horizontal transmission, shocks from meal to oil (at the median and the upper-tail) are transmitted with higher intensity relative to those in the opposite direction.

4. Conclusions and Future Research

The objective of the present work has been to investigate price linkages in the US soybean complex. This has been pursued using daily futures prices from 2015 to 2023 and a flexible econometric approach that allows modelling simultaneously both vertical and horizontal linkages at different parts of the joint distribution.

The empirical results suggest:

a) There are strong and positive vertical price linkages between soybean and its products both under large (in absolute value terms) and small price shocks. The intensity of information transmission, however, is higher downstream suggesting that (in contrast to the theory of derived demand) price changes in the soybean complex in the US are more likely to be established in the soybean market than in the meal and the oil markets. This pattern of vertical price transmission is consistent with a widening of the crush spread under shocks emanating from either the input or the final products' markets. It further indicates that processors may possess market power relative to firms operating at different levels of the complex and (for the purposes of price risk management) may make the evolution of crush spread more predictable.
b) The meal and oil prices are unconnected under large negative shocks and exhibit an inverse relationship at the median and the upper extremes. This is a direct result of their joint production in fairly fixed proportions. Given that in recent years there is a strong demand for soybean oil in the biodiesel industry, the "crushing for oil" is likely to benefit livestock producers and harm producers of substitute feedstocks such as corn silage, cottonseed meal, citrus pulp, etc.
c) Price risk transmission across all three quantile thresholds considered is asymmetric. Generally, the futures prices are more strongly connected around the median relative to the extremes of the joint distribution. A possible explanation for this finding is that market-specific factors such as the supply of the main international competitors or the global demand set a limit to the ability of domestic producers to pass very large (in absolute value terms) price shocks from one market of the complex to the others.
d) The existence of quantile-dependent linkages, along with the non-positive association between soybean meal and soybean oil prices, facilitate speculation and point to limited potential for "self-hedged" profit. It appears that soybean processors may have better, as a risk-minimising strategy, employ simple equal and opposite hedges on individual commodities in the complex.

Future works may enrich the empirical analysis by allowing for asymmetric price risk transmission, not only across the quantiles of the joint distribution but across frequencies as well. Barunik and Kley (2019) showed that this is possible for bi-variate distributions. Market networks in the real world, however, typically involve multiple markets. Therefore, additional research on this elaborate topic is certainly warranted.

[8] This is evident from the sensitivity coefficients is Table 2.

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PRICE CLUSTERING BEHAVIOR IN VIRTUAL REAL ESTATE MARKETS

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Abstract

We analyse 21,209 intraday transactions in the virtual real estate market and document significant price clustering at round numbers 0, 00, and 000 as ending digits, consistent with the negotiation hypothesis. The clustering increases with price level and pricing uncertainty proxied by the number of buyers and sellers in the NFT market. Moreover, market venue influences price clustering dynamics. Digits 9, 99, and 999 as ending prices are overrepresented in the sample, consistent with the left digit effects. However, we do not find support for the psychologically feeling right hypothesis or the strategic trading hypothesis.

JEL: O30, G10, G40, R30

Keywords: Price Clustering, Virtual Real Estate, Nonfungible Tokens, Behavioral Finance

1. Introduction

Decentraland, a virtual platform operating in the metaverse, offers non-fungible tokens (NFTs) in the form of virtual land parcels via the MANA cryptocurrency. These parcels can be freely traded among users, and all transactions are securely recorded in an Ethereum smart contract. In an explorative study, Dowling (2022) analyses 4,936 trades in the Decentraland and rejects both martingale and adaptive market efficiency. In this paper, we demonstrate pricing inefficiency through a direct measure – price clustering.

Studies show that the dollar digits cluster on 0 and 5 for a variety of assets, including stocks, commodities, and cryptocurrencies (Urquhart, 2017; Hu et al., 2019).[1] For the real estate market, Morali and Yilmaz (2023) find price clustering around even figures in residential, commercial, and land markets, with infrequent use of exact prices.

Our study focuses on analysing intraday transactions involving the MANA cryptocurrency of land parcels on the NFT trading platforms Decentraland and OpenSea. We find that the ending digit of sales prices shows significant clustering in 0, which represents a round number associated with a coarser price grid that simplifies and expedites negotiations. The extent of price clustering reduces as

[1] Price clustering has been observed in markets such as stocks (Harris, 1991; Hu et al. 2017), gold (Ball et al.,1985), derivatives (Schwartz et al., 2004), IPO and SEO markets (Kandel et al., 2001; Chiao et al., 2020), analyst forecasts (Dechow and You, 2012), drug prices (Hu et al., 2022), real estate prices (Palmon et al., 2004), and foreign exchange (Sopranzetti and Datar, 2002).

the number of buyers and sellers in the NFT market increases. Moreover, price clustering varies monotonically with price levels. Additionally, we investigate the occurrence of integer pricing, specifically examining the likelihood of sales prices ending with one zero (0), two zeros (00), and three zeros (000). Through logistic regression analysis, we identify two key determinants of price clustering: the price level and the level of pricing uncertainty. Both factors contribute to a higher likelihood of rounding in sales prices.

There is also a left-digit effect for ending digits 9, 99, and 999, which are just below a change in the leftmost digit. Surprisingly, the ending digit 5 is lower in frequency compared to 9, which is inconsistent with the typical psychological preference for digits such as 0 and 5. Furthermore, we find that the ending digit 1 has the lowest proportion, which contradicts the hypothesis of strategic trading.

By conducting a comprehensive analysis of 21,209 intraday transactions within the virtual real estate market, our research reveals unique insights into market efficiency and price negotiations in the metaverse. Like conventional markets, the virtual real estate market is susceptible to behavioral biases, including the left digit effect, a phenomenon frequently observed in consumer markets.

2. Hypotheses and Data

We examine four hypotheses regarding transaction price clustering in the metaverse real estate market.

The first hypothesis focuses on price negotiation and suggests that round numbers or coarser price grids reduce search costs in negotiations by expediting price discovery (Ball et al., 1985; Harris, 1991). According to the price negotiation hypothesis, as price level or pricing uncertainty increases, we anticipate an increase in price clustering.

The second hypothesis pertains to psychological factors, as rounded numbers are associated with a sense of "feeling right," while non-rounded numbers are more cognitively oriented. The preferred order for selecting ending digits is as follows: 0, 5, and others. Wadhwa and Zhang (2015) argue that people opt for round numbers because they find them psychologically appealing and easier to recall. However, the psychologically feeling right hypothesis would not predict positive correlations between price clustering and price level or pricing uncertainty.

The third hypothesis, known as the strategic trading hypothesis, asserts that individuals strategically choose prices by opting for values just above or below round numbers (Sonnemans, 2006). For instance, when prices cluster at 10-unit increments, strategic traders might gain an advantage by placing buy (sell) orders at the ending digit 9 (11).

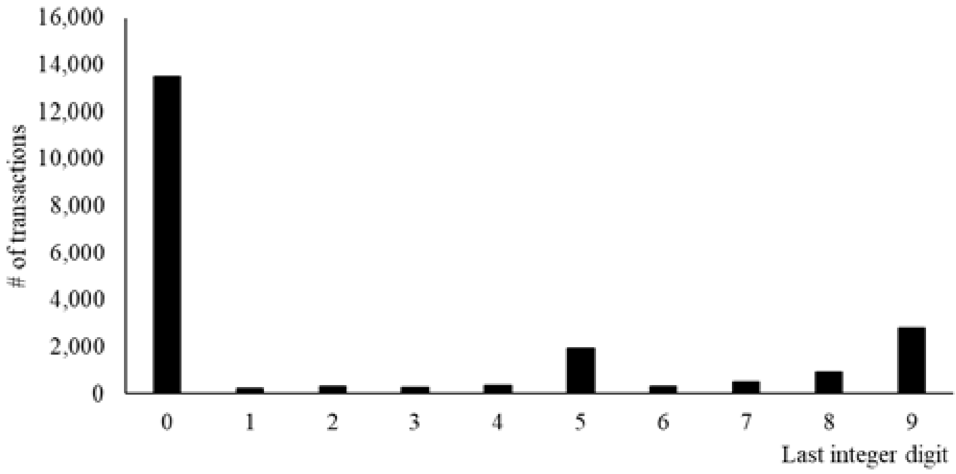
The fourth hypothesis focuses on the left digit effect, which has been examined by Manning and Sprott (2009) in relation to its impact on consumer choices. Their findings indicate that price endings on 9 have an influence on consumer behaviour. For instance, when comparing prices like 1.99 and 2.00, the left digits are 1 and 2, respectively. Thomas and Morwitz (2005) argue that consumers often exhibit behaviour characterised by being conscious of smaller expenses (penny-wise) but less concerned about larger ones (pound-foolish). Based on the left-digit effect hypothesis, we anticipate observing a higher proportion of prices ending with the digit 9. However, the strategic trading hypothesis suggests that both 1 and 9 would have higher frequencies as ending digits.

To test these hypotheses, we collect virtual real estate intraday transaction data utilising the methodology outlined by Nadini et al. (2021). Our dataset comprises 21,209 intraday transactions spanning from October 11, 2018, to April 11, 2021. We obtain the number of unique buyers and sellers in the NFT market for investor interest from https://nonfungible.com/market-tracker. The cryptocurrency MANA prices, and the S&P 500 market data are from Yahoo! Finance.

3. Results and Discussions

Do prices of virtual lands display clustering behaviour? Figure 1 illustrates the transaction frequency for prices ending in digits 0 through 9. Notably, prices ending in 0 exhibit the highest frequency, followed by prices ending in 9 and 5.

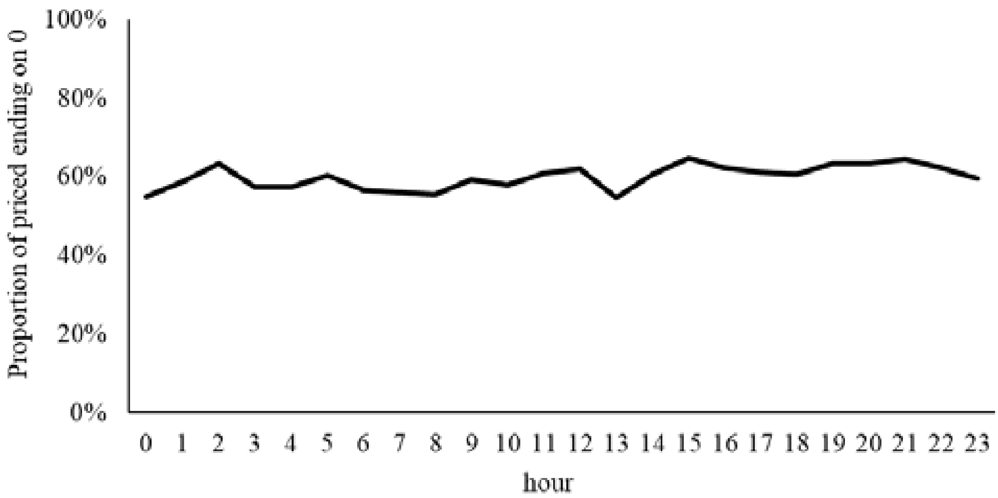
Figure 1: Distribution of the ending integer digit for virtual land prices



Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). We provide an overview of the distribution of ending integer digits for virtual land prices denominated in MANA dollars.

Figure 2 shows the intraday variations in price clustering, specifically focusing on prices ending in 0 within hourly intervals. The clustering pattern remains consistent throughout the 24-hour day. These findings align with previous studies on cryptocurrency price clustering conducted by Hu et al. (2019) and Quiroga-Garcia et al. (2022).

Figure 2: Intraday variations in price clustering



Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). We illustrate the proportion of prices ending on 0 throughout the day by hourly intervals using the UTC time.

Table 1 presents the frequencies of four different types of ending digits in the prices of virtual lands. For fractional prices, we truncate the values to four decimal places. It is worth noting that 12.6% of prices end in a fraction.[2] Within this group of 2,671 transactions, 1,085 or 40.6% of them end with .9999, providing support for the left digit effect hypothesis. However, the majority of prices (87.4%) for virtual lands end in integer values of the MANA currency.

Table 1: Price Clustering for Virtual Land Parcels

Panel A: Overall sample								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decimal	Count	Percent	Last one integer digit	Percent	Last two integer digits	Percent	Last three integer digits	Percent
.0000	1,567	7.4%	0	63.7%	00	43.5%	000	21.0%
.0001	8	0.0%	9	13.2%	99	8.2%	500	9.4%
.002	3	0.0%	5	9.2%	50	7.6%	999	5.3%
.1910	1	0.0%	8	4.5%	10	3.9%	900	3.7%
.3455	1	0.0%	7	2.5%	90	2.4%	010	3.5%
.5	1	0.0%	4	1.6%	15	1.7%	800	1.9%
.7886	1	0.0%	2	1.4%	88	1.5%	015	1.6%
.8019	1	0.0%	6	1.4%	30	1.4%	200	1.5%
.9	1	0.0%	3	1.3%	25	1.3%	100	1.4%
.99	1	0.0%	1	1.1%	80	1.3%	400	1.3%
.998	1	0.0%			Other	27.1%	Other	49.4%
.9999	1,085	5.1%						
Total obs with decimals	2,671	12.6%						
Grand total obs					21,209			

Panel B: Strategic trading vs. left digit effect			
Last integer digit	Chance proportion	Actual proportion	Difference
1	10.0%	1.1%	-8.9%***
9	10.0%	13.2%	3.2%***

Note: This table reports the summary statistics for the variables in this study. All variables are in a monthly frequency. The time span is from January 2008 through December 2014. The variables are as follows: ADR mispricing, investor attention (Wikipedia country page views are the proxy of investor attention), volume, market value, absolute returns (|Returns|), inverse price (1/P), dividend yield and the crisis dummy that assumes the value of 1 between January 2008 and June 2009, and zero otherwise. The data on ADRs is obtained from DataStream. The country-specific investor attention measure, Wikipedia page views, is obtained from the Wikipediatrends.com website.

In the real estate market, prices often end with triple zeros (000) to facilitate negotiation and price formation. Analysing the rightmost one, two, and three digits of prices in the integer MANA group, we find that ends in 0, 00, and 000 prevail over other digits. Notably, 21.0% of prices end with 000, which is comparable to the 19.6% reported by Palmon et al. (2004) for real estate listing prices clustering on 000, but much lower than the 50.5% clustering on 000 for transaction prices.

We also observe an overrepresentation of ending digits 9, 99, and 999 compared to other digits. These proportions are consistent with the left digit effect hypothesis, as the frequencies of 9 and 99 immediately trail the frequency of prices ending in round numbers 0 and 00. Since digit 5 ranks after

[2] The transactions with fractional price endings are associated with items for sale in the virtual land.

9, the findings do not support the hypothesis that digit 5 would have a higher proportion due to its psychological appeal.

To test the strategic trading hypothesis, we compare the ending digits 1 and 9 to their chance proportions using one proportion z-tests. Table 1, Panel B reveals that the proportion of ending digit 1 is significantly lower than the chance frequency. Furthermore, it ranks last in Panel A, Column (4). These results support the use of a coarser price grid to reduce search costs but reject the strategic trading hypothesis.

To further investigate the negotiation hypothesis, we analyze price clustering behaviour across different price levels and in relation to pricing uncertainty. Table 2 presents the findings on price clustering by price level. We sort the sample by transaction prices and partition the sample into three equal categories: low, medium, and high price groups. The results show that clustering in round number 0 as the ending digit increases monotonically from 39.4% for the low-price group, to 69.9% for the medium-price group, and further to 81.8% for the high-price group. Conversely, clustering around digits 9 and 5 decreases as the price level rises.

Table 2: Price Clustering for Virtual Land Parcels by Price Level

	Price level		
Last integer digit	Low (avg= 76 MANA, N=7069)	Medium (avg= 6,360 MANA, N=7070)	High (avg= 41,999 MANA, N=7070)
0	39.4%	69.9%	81.8%
1	2.1%	0.7%	0.6%
2	3.3%	0.7%	0.3%
3	2.6%	0.9%	0.5%
4	3.5%	0.8%	0.4%
5	18.9%	5.6%	3.1%
6	2.6%	1.0%	0.7%
7	4.8%	1.8%	1.0%
8	7.2%	4.2%	2.0%
9	15.6%	14.3%	9.6%

Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). The transactions are denominated in MANA cryptocurrency. Column 1 shows the MANA dollar digit of the land prices. We partition the sample based on price level into three categories: Low, Medium, and High. The average price is in parentheses under each category. Count refers to the number of observations for each digit. Percent is Count divided by the total number of observations.

Table 3 focuses on price clustering in relation to pricing uncertainty, which is proxied by two measures. The first measure is the market venue for the transactions. Investors can either use the NFT trading platform OpenSea or buy land directly through the Decentraland Marketplace. Bessembinder (1999) documents higher adverse selection costs for Nasdaq-listed stocks compared to NYSE-listed stocks. In our study, using z-tests to compare the difference in proportions between Decentraland and OpenSea, we find significantly higher price clustering in the secondary market Opensea, relative to the primary market Decentraland, which suggests that the secondary market entails more uncertainty.

Table 3: Price Clustering for Virtual Land Parcels by Price Level by Uncertainty Measures

Panel A: By market				
Last integer digit	**Decentraland**	**OpenSea**	**Difference**	
0	60.2%	77.3%	17.1%	***
1	1.2%	0.7%	-0.5%	**
2	1.7%	0.6%	-1.1%	***
3	1.5%	0.6%	-1.0%	***
4	1.9%	0.3%	-1.6%	***
5	10.8%	2.8%	-8.0%	***
6	1.5%	1.2%	-0.3%	
7	2.8%	1.3%	-1.5%	***
8	4.6%	3.9%	-0.8%	*
9	13.7%	11.3%	-2.4%	***

Panel B: By investor interest			
	Investor Interest		
Last integer digit	**Low**	**Medium**	**High**
0	75.4%	60.3%	55.4%
1	0.8%	1.3%	1.4%
2	0.5%	1.4%	2.4%
3	0.6%	2.1%	1.3%
4	0.5%	2.1%	2.1%
5	3.8%	11.1%	12.7%
6	0.9%	1.3%	2.0%
7	1.2%	2.6%	3.7%
8	4.0%	4.5%	5.0%
9	12.3%	13.3%	14.0%

*Note: We collect intraday transaction data for virtual land using the methodology outlined by Nadini et al. (2021). The transactions are denominated in MANA cryptocurrency. We use two measures of uncertainty: market venue and investor interest. Decentraland is the main market that is associated with more information relative to the secondary market Opensea. For investor interest, we use the aggregate number of unique buyers and sellers in the NFT market from https://nonfungible.com/market-tracker. We partition the sample based on investor interest into three categories: Low, Medium, and High. Count refers to the number of observations for each digit. Percent is Count divided by the total number of observations. *, **, and *** indicate significance levels based on p-values derived from z-tests to compare the difference in proportions between Decentraland and OpenSea at 10%, 5%, and 1%, respectively.*

The second measure of pricing uncertainty is investor interest, calculated as the aggregate number of buyers and sellers in the NFT market. Information production increases as more participants enter the market, reducing uncertainty. Table 3, Panel B, illustrates a monotonic decrease in price clustering with the intensity of investor interest.

To analyse the determinants of price clustering in a multivariate analysis framework, we employ logistic regressions with a binary dependent variable for price clustering as shown below.

*Price Clustering = a + b1*Medium price + b2*High price + b3*Market + b4*Investor interest*

*+ b5*MANA volatility + b6*Stock market volatility*

The dependent variable *Price Clustering* is *zero-ending*, which takes on a value of 1 if the price ends with zero and 0 otherwise. Table 4 reports the results for the logistic regression. After controlling return volatilities in the cryptocurrency and stock markets, we find statistically significant coefficients for price level and the uncertainty measures at the 1% level based on p-values derived from the Wald statistic. By comparison, Morali and Yilmaz (2023) also find increases in rounding as price levels go up. These results provide support for the negotiation hypothesis.

Table 3: Price Clustering for Virtual Land Parcels by Price Level by Uncertainty Measures

Variable	Coefficient	
Intercept	-0.270	***
Medium price	1.307	***
High price	1.928	***
Market	0.278	***
Investor interest	0.022	
MANA volatility	-0.170	***
Stock market volatility	-0.046	
N	21,209	
p-value of likelihood ratio	<0.0001	

Note: To analyse the determinants of price clustering in a multivariate analysis framework, we employ logistic regressions with a binary dependent variable for price clustering as shown below.

*Price Clustering = a + b1*Medium price + b2*High price + b3*Market + b4*Investor interest*

*+ b5*MANA volatility + b6*Stock market volatility*

*The dependent variable Price Clustering is zero-ending, which takes on a value of 1 if the price ends with zero and 0 otherwise. The explanatory variables include price dummies and proxies for uncertainty along with control variables. We rank the transactions by price into three groups. If it is in the middle group, dummy variable Medium Price is 1 and 0 otherwise. If it is in the high-priced group, dummy variable High Price is 1 and 0 otherwise. Dummy variable Market is 1 for transactions in the secondary market Opensea and 0 for transactions in the primary market Decentraland. For investor interest, we use the aggregate number of unique buyers and sellers in the NFT market from https://nonfungible.com/market-tracker. We partition the sample based on investor interest into three categories: Low, Medium, and High, and use the ranking as dummy variable Investor interest. Control variables include daily return volatilities of prior month for both the MANA and the stock market proxied by the S&P 500 index. *, **, and *** indicate significance levels based on p-values derived from the Wald statistic at 10%, 5%, and 1%, respectively.*

4. Conclusion

In the context of virtual real estate transactions, our findings reveal significant price clustering at round numbers such as 0, 00, and 000, which provides strong support for the negotiation hypothesis. These results are consistent with the observed price clustering patterns in the tangible real estate market. Additionally, we observe evidence of left digit effects, as digits 9, 99, and 999 appear with higher frequencies as ending prices. However, we do not find support for the psychologically feeling right hypothesis or the strategic trading hypothesis. These findings suggest that factors other than psychological appeal or strategic trading behaviour play a more prominent role in price clustering within the virtual real estate market.

Overall, our results lend support to the negotiation hypothesis and the left-digit effect hypothesis. Furthermore, our analysis reveals lower price clustering on Decentraland compared to Opensea as the venue for virtual land transactions. This highlights the potential influence of the market venue on price clustering dynamics. Our research offers both theoretical and practical insights. Theoretical findings reveal the significance of price clustering and the persistence of behavioural biases in the virtual real estate market, providing a bridge between the real and virtual worlds in terms of human decision-making. For practitioners and regulators, price clustering studies help in designing the virtual real estate market to encourage liquidity, facilitate negotiations, and reduce search costs. Future studies could explore the impact of virtual land location on price clustering in order to gain further insights into this phenomenon.

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THE COMPETING-RISK ANALYSIS OF POST-IPO DELISTINGS

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Abstract

This paper aims to investigate the impact of a set of covariates on the future status of IPO firms in the United States. After going public, these firms could be delisted for two primary reasons: merger and acquisition or liquidation and bankruptcy. Because these two reasons are mutually exclusive, we can implement a competing risk analysis to examine how the likelihood of delisting could be affected. There are two main findings in this paper. First, we find that the inclusion of the aftermarket performance in a competing-risk model helps distinguish the impact of those covariates on the two types of delistings. For example, profitability increases the chance of being delisted due to mergers, whereas decreases the chance of being delisted due to bad performance. Second, our evidence indicates that time-varying covariates may impact the delistings in different ways. For instance, profitability appears to affect the delistings due to merger and acquisition only until last year before delisting. In sum, our paper contributes to the literature by shedding new light on how to predict the delisting rates more accurately.

JEL: G20, G33, G34

Keywords: IPO, Delisting, Competing-risk

1. Introduction

Initial public offering (IPO, hereafter) has been intensively studied as one of the most significant corporate events. One strand of studies focuses on a major risk after firms go public, namely delisting risk. It refers to the probability that an IPO could be delisted from the exchanges. It is common to observe a firm being delisted after going public. For example, Lowry et al. (2017) show that more than 20 percent of annual cohorts of IPOs per year could be delisted in the United States. The prior literature has also well documented that delisting could entail significant consequences for shareholders. For instance, Macey et al. (2008) show that, on average, delisting from the exchanges such as NASDAQ/NYSE may cause a drop in price by about 50 percent and an increase in volatility by around 100 percent. Thus, accurate prediction of the delisting rate is significant for investors, especially institutional investors with the IPO shares allocated on the primary market.

The delisting may be triggered by different events, including merger and acquisition, migration to another exchange, liquidation, and bankruptcy. Many studies have investigated some factors as determinants of delisting rates after firms go public. However, most of these studies exclusively examine non-mutually exclusive risks. To the best of our knowledge, no work has been done by simultaneously examining multiple reasons for delistings in an integrated framework.

Thus, the first motivation of this paper is to fill this gap by implementing the competing-risk analysis of IPOs in the U.S. between 1980 and 2021. We believe such a model can enhance the prediction of delisting rates by treating different reasons for delistings as competing events because they are mutually exclusive to each other. In other words, one which occurs first causes the delisting of IPO firms, preventing other events from happening completely. For example, a firm cannot default if it has already been delisted because of an acquisition. As the prior literature suggests (e.g., Cressy et al., 2014), competing-risk analysis allows us to assess the delisting rate due to a specific event of interest more accurately while controlling for the effect of other competing-risk events simultaneously. We believe that such a model is more suitable for our analysis because of the interdependence among the possibilities of multiple cause-specific delistings.

Our paper is also motivated by the fact that the previous literature has focused on predicting the future states of IPO firms, only using the data available before the IPO or at the IPO date. Several papers find that a set of variables, such as firm size and age, can be used to forecast whether the IPO firm survives or delists. However, up to date, no study has included post-IPO financial accounting data in such analysis.

We believe that the post-IPO multi-period financial and accounting variables might be helpful in terms of more accurate prediction of post-IPO delistings. As suggested by the prior literature, the first few years after going public are crucial for IPO firms because they are exposed to significant changes in a business environment in terms of the possibility of being acquired, regulation requirements, and so on. Consequently, these firms may also show dramatic changes in their properties, such as profitability. Thus, we believe that the time-varying post-IPO data can provide new information on firm performance during the first several years after being public. Such information is not available on the IPO-deal properties.

In addition, the prior literature (e.g., Bharath et al., 2009; De et al., 2012) has shown that it is not unusual for public firms to time their significant decisions, such as merger and acquisition events, after going public. The managers will weigh the benefits and costs between remaining public and going private. Such decision-making processes are time-varying and dynamic, depending on after-market circumstances in terms of financial accounting variables, including profitability, leverage, operating expenses, and so on.

In sum, the main focus of our study is to assess post-IPO delistings due to different reasons based on the information provided by financial accounting covariates, which are updated periodically after going public. We also include the IPO deal-related characteristics at the IPO time in our analysis to be consistent with the prior literature.

The most widely used method to deal with the competing-risk dataset (e.g., Kalbfleisch et al., 1980; He et al., 2010) is to estimate the model separately for each type of failure while treating the different events as censored data. However, Lunn et al. (1995) argue that one drawback of the Kalbfleisch et al. (1980) method is that it does not treat the different risks jointly. Therefore, in this paper, we implement the method proposed by Fine et al. (1990) to fit a competing risk model to panel data of initial public offerings consisting of 7,438 IPOs from 1980 through 2022.

We classify all the delistings into two groups according to their reasons, which triggered the delistings. The information on all the delisting reasons is provided by the CRSP delisting codes. Based on delisting codes, there are three categories of aftermarket status of new firms after going public, including "active", "delisted due to acquisition/merge", and "delisted due to bad performance". Here, we also refer to bad performance as liquidation or bankruptcy.

By taking competing-risk events into account to describe the effect of covariates on post-IPO delistings due to the two reasons, our study contributes to the current literature on IPO failure risk in two aspects. First, we apply the competing-risk model to the IPO panel data, which includes both IPO-deal related properties at the IPO date and annually updated accounting information after going public. To our understanding, such analysis has yet been done. The competing risk analysis on the IPO panel data can help predict the possibility of delisting due to different reasons, more precisely, in terms of both the algorithm of the duration model and the amount of information.

Second, the prior literature (e.g., Bharath et al., 2009; Gao et al., 2013; McDonald et al., 2022) has provided some implications on how firms make the decision to exit from public markets. For example, Bharath et al. (2009) argue that firms weigh the costs and benefits of being public in the decision to go private. However, limited evidence has been provided on how time-varying factors affect the decision on voluntary delistings. Moreover, our sample shows that around 50% and 80% of delistings occurred within 5 and 10 years after the initial public offerings, respectively. Thus, it is interesting to view the pattern of time-varying covariates during the first five years after going public. Doing so helps our understanding of how the delistings are affected by those time-varying factors.

The results show that, by including the aftermarket annual accounting information, the competing-risk model can help distinguish the impact of those covariates on the delistings for three reasons. There are two main findings from our analysis. First, it is found that two time-varying covariates, including profitability and leverage, have opposite effects on different events triggering the delisting, either acquisition/merger or liquidation/bankruptcy. The increase of these covariates could increase the possibility of delisting generated by acquisition/merge but reduce the risk of delisting due to failure, either liquidation or bankruptcy. Second, we find that IPO firms which were delisted triggered by acquisition/merger only underperformed the surviving IPOs until last year before delistings. On the other hand, the IPOs delisted due to failure underperformed the surviving IPOs significantly and consistently across the whole period as being listed on public markets. Putting two and two together implies that the decision to exit the public markets through acquisition/merger is made only when firm performance is worse than comparable new firms at the same post-IPO stages.

In sum, the contribution of this paper is to provide new evidence on how we can make the prediction of post-IPO delistings more accurately by implementing competing-risk analysis and viewing the time-varying factors within the first several years after going public. The remainder of this paper proceeds as follows. Section 2 provides the literature review. Section 3 defines the hypotheses we like to test in this paper. Section 4 introduces the data and the methodologies implemented in our study. The empirical results and conclusions are summarised in Sections 5 and 6, respectively.

2. Literature Review

The delisting risk, also called failure risk, has been a hot topic understudies so far (e.g., Hensler et al., 1997; Algebaly et al., 2013; Colak et al., 2022; Espenlaub et al., 2012; Fu et al., 2023; Gilbey et al., 2013; Kim et al., 2019; Makrominas et al., 2021; Park et al., 2018). Many researchers suggest that some information available before the issuance or at the IPO date is related to the future state of the firm after going public. For example, Hensler et al. (1997) find that the survival time for IPOs increases with some firm properties, including firm size, age of the firm at the offering, the initial return, the IPO activity level in the market, and the percentage of insider ownership. Their results of duration models also show that survival is negatively related to other factors, such as the number of risk characteristics.

Fama et al. (2004) investigate the characteristics of new firms listed on major U.S. stock markets from 1973 to 2001 and find that both declining profitability and increasing growth lead more IPO firms to be delisted due to bankruptcy but have no impact on the possibility of IPO firm delisted due to acquisition/merge. Therefore, their results imply that both profitability and growth could be good candidates to distinguish between the survival and failure of IPO firms.

Howton (2006) studies the relationship between a firm’s governance characteristics and the post-IPO state. His results show that IPO firms that are venture-backed have a CEO who is the original firm founder, have an outside block holder present, use a more reputable underwriter, and have a more stable board directors are more likely to survive than be acquired in the first five years after the IPO whereas a larger percentage of grey directors on the board are associated with IPO firms that are more likely to fail. His analysis is performed by fitting one Logistic regression between each pair of three future states after going public, consisting of “survive”, “delisted due to takeover”, and “delisted due to failure”.

Demers et al. (2007) study the survival rate of IPO firms by including IPO-deal characteristics and accounting information at the IPO time. The information that they used to predict the survival rate of IPOs is available around the issuing date. Moreover, they find that the possibility of IPO failure estimated by the logit model is negatively associated with one-year post-IPO abnormal returns. In other words, the information on IPO failure is not complete at the IPO date, implying that more post-IPO information is necessary for a more precise estimate of IPO failure.

Another school of recent literature put more focus on how IPO delistings are related to merger and acquisition events. As proposed, going public has been used as one way to accomplish the consequent acquisitions. For example, De et al. (2012) investigate why firms become acquisition targets shortly after their initial public offerings.

However, very few studies in IPO literature have attempted to assess the delisting risk by using the post-IPO accounting information over multiple periods after going public in the duration models. Therefore, examining whether or not including the aftermarket accounting numbers improves the predictability of duration models on the future status after going public is interesting.

3. Hypotheses: Competing Hazard of Delisting

In this study, we examine the impact of some variables on the likelihood of post-IPO delistings due to two primary reasons. Following the prior IPO literature, we consider two sets of covariates as potential determinants: fixed and time-varying. For example, Demers et al. (2007) include IPO-deal characteristics as fixed determinants, composed of a technology dummy, venture-backed dummy, underpricing, IPO proceeds, and number of IPOs per quarter. These covariates are defined as fixed since their values will remain unchanged once the issue has been finished at the IPO time. They also include the accounting determinants in their models to predict the IPO failure risk. However, they only estimate their models based on the accounting information over a single period around the issuing time. In other words, the information contained in annual financial statements after going public has not been considered in their study.

Unlike Demers et al. (2007), we are attempting to include more updated information to predict the chance of delisting possibility by adding the post-IPO financial accounting information, which is updated annually after going public. This group includes firm age, firm size, profitability, growth, research and development expenses, selling, general and administrative expenses, and leverage.

In sum, we include two sets of determinants in our competing-risk models: IPO deal-related characteristics, which are fixed at the IPO time, and aftermarket accounting variables, which are updated periodically. Therefore, there are multiple observations for each sample firm with time-varying accounting variables but fixed IPO deal-related properties.

The main purpose of this paper is to investigate the impact of a group of factors on delisting due to either (1) merger and acquisition or (2) bad performance, respectively. Therefore, drawing on the findings from the extant literature, our hypotheses on variables of interest are summarised as follows.

H1. Presence of Venture-Capital Firm

Many studies (e.g., Jain et al., 2000; Brav et al., 1997; Gill et al., 2016; Gomulya et al., 2016; Iliev et al., 2020; Pommet et al., 2017) have shown that venture capital firms improve the aftermarket performance of IPO firms. For example, both Jain et al. (2000) and Brav et al. (1997) argue that VC-backed IPOs outperform non-VC-backed firms, although the conclusion of the latter only holds when returns are weighted equally. Thus, we expect that VC-backed IPO firms are less likely to be delisted due to bad performance, either liquidation or bankruptcy, than non-VC-backed IPO firms.

Howton (2006) finds that a venture-backed IPO firm is more likely to survive rather than delist after a takeover, which can be explained by the post-IPO presence of the venture firm on the board, as proposed by Brav et al. (1997). On the other side, other studies find that institutional investors such as venture capital may use merger and acquisition as the option to cash out of the IPO firm and exit (e.g., De et al., 2012). Put these two together, and we do not have a specific prediction on the effect of venture capital firms on post-IPO delisting due to mergers and acquisitions. In sum, we propose the following hypothesis:

H1: VC-backed firms are less likely to be delisted due to bad performance, while the presence of venture capital firms does not affect the probability of delisting due to mergers and acquisitions.

H2. IPO Underpricing

The literature is still mixed about how to interpret the issue of IPO underpricing. IPO underpricing has been attributed to investors' uncertainty, signalling of firm quality by managers, or timing of primary market by managers. Therefore, we do not have a specific prediction on the effect of IPO underpricing on the post-IPO delisting, no matter how it is triggered. The hypothesis is defined as follows.

H2: IPO underpricing does not affect the probability of delisting due to either bad performance or merger and acquisition.

H3. Firm Size

Firm size has been proven to be a key issue when the firms are making decisions on takeover or other issues. The prior literature has documented that a larger firm is more likely to survive because of a lower default risk. Therefore, we expect that firm size can reduce the likelihood of delisting, no matter how it is triggered. The hypothesis is defined as follows.

H3: Larger firms are less likely to be delisted due to bad performance or merger and acquisition.

H4. Profitability

As proposed by Fama et al. (2004), we expect that profitability should help reduce the risk of delisting triggered by bad performance, either liquidation or bankruptcy. Meanwhile, their study did not find a significant association between profitability and the delisting risk originating from mergers and acquisitions. Thus, we do not provide specific predictions on how profitability may affect the delisting due to merger and acquisition. The hypothesis is proposed as follows.

H4: Firms with higher profitability are less likely to be delisted due to bad performance, while a firm's profitability does not affect the probability of delisting due to merger and acquisition.

H5. Research & Development (R&D) Expenses

Following the prior literature (e.g., Demers et al., 2007; Fedyk et al., 2018; Kim et al., 2021; Wu et al., 2021), we include R&D expenses to capture the scale of the firm's expenditures on R&D. The effect of R&D expenses on delisting risk could be either positive or negative. On one side, more R&D expenses may provide more growth opportunities for the IPO firm, indicating a negative link between R&D expenses and the delisting risk, i.e. R&D expenses will reduce the possibility of IPO firms being delisted after going public. On the other side, a higher level of R&D expenses could imply the management inefficiency of the assets-in-place. Therefore, it is hard to predict the direction of how R&D expenses will affect the delisting risk due to both reasons. We propose the hypothesis on R&D expenses as follows.

H5: Research & Development (R&D) Expenses do not affect the probability of delisting due to either bad performance or merger and acquisition.

H6. Selling, General, and Administrative (SG&A) Expenses

The same story applies to another variable, selling, general, and administrative (SG&A) expenses, with the exception that SG&A expenses are related to intangible assets. Again, the firm may benefit from more SG&A expenses if investing in intangible assets can create real future growth opportunities. Otherwise, higher SG&A expenses may do harm to the firm's performance, leading to a higher possibility of being delisted. Similarly, we do not provide any specific prediction on how SG&A expenses will affect the delisting risk due to both reasons. We propose the hypothesis on SG&A expenses as follows.

H6: Selling, General, and Administrative (SG&A) Expenses do not affect the probability of delisting due to either bad performance or merger and acquisition.

H7. Leverage

It has been documented that leverage plays an important role in predicting either a new firm's post-IPO status or a seasoned firm's default risk. Consistent with the findings in the prior studies, we expect a positive effect of leverage on the probability of delisting due to bad performance since higher leverage would increase default risk, leading to more delistings. On the other side, we do not have a specific prediction on the effect of leverage on the post-IPO delisting due to merger and acquisition. Put these together, we propose the following hypothesis:

H7: Firms with higher debt ratios are more likely to be delisted due to bad performance; meanwhile, borrowing more does not affect the probability of delisting due to mergers and acquisitions.

4. Data and Methodologies

4.1. Data

Our data collection originates from 9,396 IPOs from Jay Ritter's IPO database from 1980 through 2022, containing each firm's founding date and first trading date. The information on the date of the issue, the dollar value of proceeds raised, and the percentage change in the stock price on the first trading day (underpricing) are collected from the Securities Data Company (SDC) Database. Following Fama et al. (2003), our sample excludes REITs, closed-end funds, ADRs, unit offers, MLPs, and all issues with an offer price below 5 dollars. The SDC dataset covers the new issue in the United States from 1985 to 2022. We obtain the annual financial data for these IPO firms from the CRSP and COMPUSTAT databases.

To be included in the final sample, the firms must have unique 6-digital CUSIP identification across JayRitter/SDC/CRSP/COMPUSTAT datasets to ensure the data availability of all the data required for our analysis. There are about 80% matches between CRSP and COMPUSTAT among the initial list of 13,945 IPO firms from Jay Ritter. Then, about 6,507 firms are deleted due to the mismatches between SDC and CRSP/COMPUSTAT and 7,438 firms remain in our final sample for survival analysis.

Table 1 defines all the variables used in this paper. The variables include the IPO deal-related characteristics, which are fixed at the IPO date once the issue has been finished, and the post-IPO financial data, which are time-varying.

Table 1: Variable Definitions

Variable name	Definition
Survival time (months)	Number of months traded on the exchanges after IPO
Failure	One if the firm delisted due to failure after IPO, zero otherwise
Merger & Acquisition	One if the firm delisted due to acquisition/merge after IPO, zero otherwise
Venture dummy	One if venture firm backed, zero otherwise
Underpricing (%)	Initial return for the first trading day
Proceeds ($ millions)	Natural log of one plus Proceeds from the IPO in million dollars
IPO activity	Number of IPOs per quarter
Age (years)	Natural log of one plus Firm age in years
Firm Size ($ millions)	Natural log of one plus market value of common shares outstanding
Profitability (%)	Net income divided by total assets
Growth (%)	Growth in total assets, measured as percentage change in total assets
R&D expense (%)	R&D expenses divided by total assets
SGA expenses (%)	Selling, general, and administrative expenses divided by total assets
Leverage (%)	Total liabilities divided by total assets

Note: This table defines two sets of variables used in this paper, including (1) the variables related to IPO-deal characteristics and (2) the time-varying accounting variables regarding firm properties. The sample period is between 1980 and 2021

The aftermarket status of IPO firms is classified by their CRSP delisting codes. The firms are identified as "active" if their delisting codes are 100, "delisted due to merger and acquisition" if their delisting codes are in the 200 range, and "delisted due to move to another exchange" if their delisting codes are in the 300 range. The 200s indicate "acquired in merger", and the 300s indicate "issues acquired by exchange of stock". The firms are classified as "delisted due to bad performance" if their delisting codes are in the 400 range or 500 range, which we refer to bad performance as liquidation or bankruptcy. However, 55 firms whose delisting codes are from 501 to 520 and one with 575 are dropped from the final samples. Table 2 shows the status of all the remaining 7,438 IPO firms in the final sample.

Table 2 shows there are 5,432 delistings among 7,438 IPO firms from 1980 to 2021, including 3,780 acquisition/merge delistings and 1,652 failure delistings. Consistent with Fama et al. (2004), the number of IPO firms on major U.S. stock markets increased in general from the 1970s to the post-1980 periods. Table 3 summarises the data.

Table 2: Status of IPO Firms from 1980 to 2021

IPO year	Total	Surviving	Merger & Acquisition	Liquidation & Bankruptcy
1980	2	0	2	0
1981	2	0	2	0
1982	0	0	0	0
1983	9	0	9	0
1984	2	0	2	0
1985	4	0	3	1
1986	350	30	207	113
1987	290	20	163	107
1988	128	6	73	49
1989	121	11	70	40
1990	89	8	52	29
1991	216	20	130	66
1992	346	32	216	98
1993	488	49	295	144
1994	398	30	242	126
1995	368	24	237	107
1996	534	36	332	166
1997	382	38	223	121
1998	255	28	143	84
1999	338	33	210	95
2000	260	26	165	69
2001	36	11	22	3
2002	75	30	42	3
2003	95	35	44	16
2004	213	61	125	27
2005	158	44	91	23
2006	174	51	94	29
2007	179	47	105	27
2008	23	7	11	5
2009	64	22	34	8
2010	10	5	3	2
2011	105	33	57	15
2012	129	62	54	13
2013	189	82	92	15
2014	204	91	93	20
2015	110	63	40	7
2016	86	60	23	3
2017	131	98	24	9
2018	136	115	19	2
2019	141	121	15	5
2020	197	186	10	1
2021	401	391	6	4
Total	**7438**	**2006**	**3780**	**1652**

Note: This table shows the status of all the remaining 7,438 IPO firms in the final sample during the period from 1980-2021. There are three possible aftermarket status of IPO firms, including (1) remaining publicly traded, (2) being delisted due to acquisition or merge activities, and (3) being delisted due to bad performance. In this table, we annotate these three categories as "Surviving", "Merger & Acquisition", and "Liquidation & Bankruptcy", respectively. It shows the number of IPOs are classified within each category, among all the IPOs issued in each year. For example, in 1986, there were 350 firms going public in total, among which 30 firms remain trading actively on the exchanges, 207 were delisted due to merger and acquisition events, and 113 were delisted due to liquidation or bankruptcy, respectively.

Following Demers et al. (2007), we adjust the value for those variables, which are measured in dollar amount, back to the value in 1973 dollar values according to the annual CPI growth rate to eliminate the effect of the inflation rate on our results. Such adjustment makes our results more comparable to the current IPO literature. The descriptive statistics of variable in our study is consistent with previous studies such as Fama et al. (2004) and Demers et al. (2007). The IPO firms have an average survival time of 80.58 months and underpricing of 17.3%. Interestingly, the IPO firms are suffering a loss of -6.267% (measured by E/A) on average, most caused by those bad performance delisted IPO firms, which are suffering a loss of -21.295%.

Table 3: Descriptive Statistics for Subsamples

Variable name	Full Sample		IPOs Still Trading		IPOs Merges		IPOs Failed	
Number of firms	N=7,438		N=2,006		N=3,780		N=1,652	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Survival time (months)	80.577	70.679	105.697	79.723	64.613	59.399	58.980	52.060
Venture dummy	0.418	0.493	0.423	0.494	0.453	0.498	0.338	0.473
Underpricing (%)	0.173	0.319	0.182	0.322	0.18	0.327	0.141	0.291
Proceeds ($ millions)	3.341	1.129	3.645	1.114	3.212	1.07	2.946	1.103
IPO activity	29.515	19.09	29.866	19.051	28.975	19.268	29.860	18.780
Age (years)	16.227	20.976	17.753	23.260	15.457	18.985	14.507	19.368
Firm size ($ millions)	11.887	1.893	12.699	1.790	11.761	1.624	10.394	1.627
Profitability (%)	-6.267	29.415	-2.251	23.640	-3.125	23.919	-21.295	42.896
Growth (%)	17.746	163.506	21.353	143.512	20.428	181.632	4.533	164.358
R&D expense (%)	7.309	12.551	7.110	12.151	7.233	11.239	7.891	15.553
SGA expenses (%)	33.075	27.751	29.034	24.525	33.820	26.536	40.256	34.343
Leverage (%)	44.917	27.352	43.258	26.008	41.919	24.476	54.584	32.983

Note: This table shows the summary statistics of variables used in this paper during the period from 1980-2021. It includes two sets of variables, including (1) the variables related to IPO-deal characteristics and (2) the time-varying accounting variables regarding firm properties. We also classify all the IPOs in our sample into three groups, defined as "IPOs Still Trading", "IPOs Merges", and "IPOs Failed", respectively. Survival times refer to the number of months traded on the exchanges after going public. A venture dummy is defined as one if the IPO is backed by a venture firm, zero otherwise. Underpricing is defined as the initial return on the first trading day after going public. Proceeds are computed as Ln(1+Proceeds from the IPO in million dollars). IPO activity is measured using the number of IPOs per quarter. Age is calculated as Ln(1+Firm Age in years). Firm size is calculated as (1+Ln(MV)), where MV refers to the market value of common shares outstanding. Profitability is defined as net income divided by total assets. Growth is defined as a percentage change in total assets, calculated as (Total Assetst -Total Assetst-1)/ Total Assetst-1. R&D expenses is computed as research and development expenses divided by total assets. SGA expenses is computed as the selling, general, and administrative expenses divided by total assets. Leverage is computed as total liabilities divided by total assets.

4.2 Methodologies

As mentioned above, we believe that competing-risk analysis is suitable in case of IPO delisting. It is because two reasons for delistings are mutually exclusive to each other. If one event occurs first and causes the delisting of the IPO, the other event will never happen. For example, a firm cannot default if it has already been delisted, triggered by an acquisition. Competing-risk analysis helps assess the delisting rate due to one event by controlling for the effect of other events simultaneously because of the interdependence among the possibilities of two cause-specific delistings.

The most widely used method to deal with competing-risk datasets, proposed by Kalbfleisch et al. (1980), is to estimate the model separately for each type of failure while treating the different events as censored data. However, Lunn et al. (1995) argue that one drawback of the Kalbfleisch et al. (1980) method is that it does not treat the different risks jointly. Instead, they suggest that a data duplication method can avoid such disadvantages. For example, all the observations of their cancer datasets are counted twice in the final sample to estimate the model, one for each type of failure risk.

Based on the method proposed by Fine et al. (1999), we model the delisting rate due to reason *j* as a sub-hazard defined as

$$h_j(t|X) = \overline{h}_{j,0}(t)\, exp(\,\beta_{j,1}VCDummy + \beta_{j,2}Underpricing + \beta_{j,3}Proceeds + \beta_{j,4}IPOActivities + \beta_{j,5}FirmAge + \beta_{j,6}FirmSize) + \beta_{j,7}Profitability + \beta_{j,8}Growth + \beta_{j,9}R\&DExpenses + \beta_{j,10}SGAExpenses + \beta_{j,11}Leverage) \quad (1)$$

where *j*=1 and 2 denote the delistings due to merger and acquisition and bad performance, respectively. The dependent variable $h_j(t)$ is the instantaneous probability that a new list is delisted for reason *j, conditional on being* delisted the first time since its listing. *X* represents a set of variables, including fixed and time-varying covariates. β_j denotes the effect of covariates on the sub-hazard function caused by the *j-th* reason.

The independent variables are defined as follows. A venture dummy is defined as one if the IPO is backed by a venture firm, zero otherwise. Underpricing is defined as the initial return on the first trading day after going public. Proceeds is computed as Ln(1+Proceeds from the IPO in million dollars). IPO activity is measured using the number of IPOs per quarter. Age is calculated as Ln(1+Firm Age in years). Firm size is calculated as (1+Ln(MV)), where MV refers to the market value of common shares outstanding. Profitability is defined as net income divided by total assets. Growth is defined as a percentage change in total assets, calculated as (Total Assets$_t$ - Total Assets$_{t-1}$)/ Total Assets$_{t-1}$. R&D expenses are computed as research and development expenses divided by total assets. SGA expenses are computed as the selling, general, and administrative expenses divided by total assets. Leverage is computed as total liabilities divided by total assets.

In the following analysis, the competing risk models are estimated using the Stcrreg package in STATA, which implements the method proposed by Fine et al. (1999).

This paper also estimates a multinomial logit model on our sample as an additional test. The model is specified as

$$Logit(P_i) = \alpha_i + \beta_i X_i \quad (2)$$

where *i*=1 and 2 denote the delistings due to merger and acquisition and bad performance, respectively. X_i represents a set of variables, including fixed and time-varying covariates. B_i denotes the effect of covariates on the sub-hazard function caused by the *i-th* reason. As suggested by the previous study, such a model can help assess the likelihood of delisting due to different reasons directly.

Last, we investigate the pattern of time-varying covariates across the first several years after the initial public offerings. By doing so, we can see deeply how these factors can affect the delisting risk due to different reasons over the post-IPO period before being delisted from public firms.

5. Empirical Results

5.1 Life Table of Post-IPO Delistings

A life table is shown in Table 4, grouping the post-IPO delistings into different years. The delistings are summarised based on specific triggering events in Panel A and Panel B, respectively. Each panel tells us about the cumulative failure rate (the proportion of IPOs in the data that have been delisted due to specific reason during the interval), the average hazard rate for the interval, and the 95% confidence interval for the hazard rate (Pryce et al., 2006).

Table 4: Life Table for Time to Survive After IPO (1980-2022)

Panel A: Delisting due to Merger and Acquisition					
Time to survive (Years)		Cumulative %	Hazard	Hazard 95% Confidence Interval	
0	1	9.48%	0.0505	0.0444	0.0566
1	2	22.69%	0.0779	0.0699	0.0858
2	3	34.64%	0.0798	0.0712	0.0884
3	4	45.39%	0.0815	0.0723	0.0908
4	5	54.43%	0.0791	0.0693	0.0889
5	6	60.95%	0.0662	0.0565	0.0759
6	7	66.12%	0.0604	0.0505	0.0703
7	8	70.76%	0.0617	0.0510	0.0724
8	9	74.74%	0.0596	0.0484	0.0707
9	10	78.14%	0.0562	0.0449	0.0676
Panel B: Delisting due to liquidation					
Time to survive (Years)		**Cumulative %**	**Hazard**	**Hazard 95% Confidence Interval**	
0	1	6.57%	0.0166	0.0131	0.0202
1	2	19.42%	0.0358	0.0304	0.0413
2	3	33.18%	0.0435	0.0372	0.0499
3	4	44.04%	0.0390	0.0326	0.0454
4	5	54.51%	0.0433	0.0361	0.0506
5	6	62.23%	0.0371	0.0299	0.0444
6	7	69.65%	0.0410	0.0328	0.0491
7	8	74.62%	0.0313	0.0237	0.0390
8	9	79.43%	0.0341	0.0257	0.0425
9	10	82.42%	0.0233	0.0160	0.0307

Note: This table shows a life table as we group the post-IPO delistings into different years. The delistings are summarised based on specific triggering events in Panel A and Panel B, respectively. Each panel tells us about the cumulative failure rate (the proportion of IPOs in the data that have been delisted due to specific reason during the interval), the average hazard rate for the interval, and the 95% confidence interval for the hazard rate, following the methodologies in Pryce et al., (2006).

We see that more than half of delistings due to either reason occurred within the first five years, and a majority (around 80%) were delisted within ten years after going public. The hazard of delistings increases continuously for the first few years and then decreases gradually with some small exceptions for both reasons. The result implies that the likelihood of delistings varies during the period as being listed on public markets. It is consistent with the prior literature. For example, Bharath et al. (2009) find that firms are weighing the costs and benefits of being public to make and time the decision to go private.

5.2 Competing-risk Analysis

Next, we apply the competing-risk model to our sample, using the IPO deal-related characteristics and annual financial accounting data within 5 years after going public. We follow the method proposed by Fine et al. (1999), where the delisting rate due to reason j as a sub-hazard is defined as

$$h_j(t \mid X) = \bar{h}_{j,0}(t)\exp(Xb_j) \tag{3}$$

where j =1 and 2 for the merger and acquisition, and the bad performance, respectively. The results are reported in Table-5.

Table 5: Competing-risk Analysis of Delistings

Variable name	Delisting due to Merger and Acquisition		Delistings Due to Failure	
Venture dummy	0.2185	***	-0.2690	***
	[4.02]		[-3.29]	
Underpricing	0.0093		0.1803	*
	[0.13]		[1.66]	
Proceeds	0.1433	***	0.1144	**
	[4.27]		[2.22]	
IPO activity	0.0017		0.0009	
	[1.18]		[0.4]	
Firm age	-0.0014		-0.0117	***
	[-1.03]		[-3.82]	
Firm size	-0.0219		-0.7300	***
	[-1.17]		[-21.21]	
Profitability	0.0050	***	-0.0063	***
	[4.73]		[-7.27]	
Growth	-0.0002		-0.0001	
	[-1.15]		[-0.5]	
R&D expense	0.0002		-0.0076	***
	[0.09]		[-3.15]	
SGA expenses	0.0029	***	-0.0021	**
	[3.07]		[-2.06]	
Leverage	-0.0028	***	0.0136	***
	[-2.81]		[12.53]	
IPO Year (80-89)	-0.1196		1.0366	**
	[-0.53]		[1.99]	
IPO Year (90-99)	-0.1927		1.1040	**
	[-0.85]		[2.12]	
IPO Year (00-09)	0.0466		1.2688	**
	[0.21]		[2.42]	
IPO Year (10-19)	0.2381		1.6305	***
	[1.04]		[3.09]	
IPO Year (20-21)	-0.0115		1.6155	***
	[-0.05]		[3.00]	

Note: This table shows the results of completing-risk model specified as below.

$$h_j(t \mid X) = \bar{h}_{j,0}(t)\exp(Xb_j)$$

*The dependent variable is the likelihood of delisting due to reason j, including (1) acquisition/merger and (2) failure. The independent variables are defined as follows. Venture dummy is defined as one if the IPO is backed by venture firm, zero otherwise. Underpricing is defined as the initial return on the first trading day after going public. Proceeds is computed as Ln(1+Proceeds from the IPO in million dollars). IPO activity is measured using the number of IPOs per quarter. Age is calculated as Ln(1+Firm Age in years). Firm size is calculated as (1+Ln(MV)), where MV refers to the market value of common shares outstanding. Profitability is defined as net incomes divided by total assets. Growth is defined as percentage change in total assets, calculated as (Total Assets$_t$ - Total Assets$_{t-1}$)/ Total Assets$_{t-1}$. R&D expenses is computed as research and development expenses divided by total assets. SGA expenses is computed as the selling, general, and administrative expenses divided by total assets. Leverage is computed as total liabilities divided by total assets. *, **, ***, significant at the 10, 5, and 1 percent level, respectively.*

It is worth noting that how each covariate affects the likelihood of post-IPO delisting depends on which event triggers the delisting status. Some variables have the same impacts on two competing risk events in terms of the sign of coefficient estimates, whereas the others affect different events in different directions. There are three main findings based on the competing-risk analysis.

First, we find that only one covariate (issuing proceeds) significantly affects two competing-risk events (acquisition/merger and liquidation/bankruptcy) in the same direction. The issuing proceeds have a significantly positive coefficient estimate for both bad performance cases and takeover cases, implying that more issuing proceeds lead to a higher delisting rate. The positive effect could be attributed to the overvaluation of IPO firms, leading to an earlier delisting due to either event.

Second, four factors, including venture capital dummy, profitability, SG&A expenses, and leverage, have opposite effects on different events triggering the delisting, acquisition/merger and liquidation/bankruptcy. Specifically, the increase of these covariates could increase the risk of acquisition/merge delisting while reducing the risk of failure delisting. For example, the coefficient estimate for the venture capital dummy is 0.22 in case of mergers-related delisting risk, with a -0.27 for delisting due to bad performance, either liquidation or bankruptcy. Thus, it can be concluded that a venture capital-backed firm is more likely to be delisted due to mergers rather than survive while less likely to be delisted due to bad performance. Our results lend supportive evidence to Hypothesis-1 on venture capital dummy regarding the delistings due to bad performance.

However, our result is against the findings by Howton (2006), who finds that a venture-backed IPO firm is more likely to survive rather than delist after a takeover. He attributes his findings to the argument proposed by Brav et al. (1997), that the post-IPO presence of the venture firm on the board will reduce the delisting risk generated by a takeover. Our results prefer the opposite direction. Table 5 shows that venture dummy is significantly positively related to the possibility of delisting due to a takeover. In other words, the presence of venture capital can increase the chance for a firm to be delisted due to an event of merger and acquisition. Such a finding is consistent with another strand of the prior literature (e.g., De et al., 2012), implying that merger and acquisition has been used by venture capital firms as an approach to cash out their investment in IPO firms.

Regarding H4, the same pattern is also found for profitability, indicating that a higher firm value will increase the possibility of IPO firms being delisted caused by mergers while reducing the risk of delisting resulting from a bad performance. Our result is consistent with that of Fama et al. (2004), showing that profitability should help reduce the risk of delisting triggered by bad performance, either liquidation or bankruptcy. Meanwhile, their study implies a positive association between the growth of assets and failure rate. However, they argue that neither variable is significant for the delisting risk originating from acquisition/mergers.

Since SG&A expenses are related to intangible assets, higher SG&A expenses may do harm to an IPO firm's aftermarket performance, leading to a higher possibility of being delisted. However, our results are against the predicted direction specified in Hypothesis 6. Further study is necessary before it can be explained. Consistent with Hypothesis 7 originating from the prior studies, we find a positive effect of leverage on the probability of delisting due to failure since higher leverage would increase default risk, leading to more mandatory delistings. On the other side, lower leverage may make the IPO firms more attractive as an acquisition target.

Third, we find that some covariates, including underpricing, age, firm size, and R&D expenses, are significantly related to bad performance-triggered delisting without any impact on takeover-triggered delisting. For example, consistent with Hypothesis 2, underpricing has a positive coefficient estimate in case of failure-triggered delisting with an insignificant one for takeover-originated delisting. As we mentioned above, two theories have been suggested by the current literature to explain IPO underpricing, investor uncertainty, and signal of firm quality. The uncertainty one predicts a positive relationship between underpricing and delisting risk, while the latter expects a negative link, no matter which reason triggered the delisting after going public. Our results support the theory of information asymmetry between firms and investors partially instead of the signalling model.

Our results show that the coefficient estimates of firm age are only significantly negative for bad delistings, implying that the probability of such delisting is inversely related to firm age. This conclusion is the same as those proposed by the prior literature, for example, Schultz (1983) and Hensler et al. (1997). Specifically, older firms are more likely to survive than delist.

As mentioned in Hypothesis-3, firm size has been documented as a key issue when the firms are making decisions on takeover or other issues. A larger firm is more likely to survive than delisted due to liquidation or bankruptcy because of a lower default risk, which is supported by our result. On the other side, we find no evidence to show that a larger firm is more likely to be involved in a takeover event.

In terms of Hypothesis 5, we find that R&D expenses will reduce the possibility of delisting due to failure based on our analysis. The negative link between R&D expenses and delisting risk supports the findings of Demers et al. (2007), who argue that higher R&D expenses mean a higher growth opportunity for the IPO firm. On the other side, such a result contradicts the theory of the management inefficiency of the assets-in-place, which predicts a positive link between R&D expenses and delisting risk.

Moreover, we also find that two variables, IPO activity and asset growth, are not significantly related to the likelihood of post-IPO delistings due to either reason. As for IPO activities, it is consistent with other studies, such as Hensler et al. (1997), who found no evidence to support the timing effect on the delisting risk in their study. However, Ritter (1990) argues that firms are attempting to raise capital when the cost of equity is relatively low during the hot time.

The coefficient estimates for the asset growth are inconsistent with the findings in Farm et al. (2004). In other words, the new firms are more likely to fail because of a high growth rate of total assets, which may be explained by overinvestment.

Put together, we can find that factors have a different impact on the delisting due to two different reasons. Therefore, it is essential and helpful to consider competing-risk events to help predict the future states of new firms after going public.

5.3 Multinominal Logit Model

Here, we estimate a multinomial logit model on our sample as an additional test. The model is defined as

$$Logit(P_i) = \alpha_i + \beta_i X_i \tag{4}$$

where P_i=1 and 2 denote the delisting rates due to merger and acquisition and bad performance, respectively. X_i represents a set of variables, including fixed and time-varying covariates. B_i denotes the effect of covariates on the sub-hazard function caused by the *i-th* reason. The results are reported in Table 6.

Table 6 shows that most of the results from the multinomial logit model remain similar to those from competing-risk analysis, except for several variables. For example, the coefficient estimates of the venture dummy are insignificant for both groups of delisting, showing that venture capital firms have no significant impact on the delisting rate, no matter the triggering event. Another example is asset growth, which appears to be significantly positively related to the delisting rates in both groups. The difference between the two methods may be driven by how two groups of delistings are treated when estimating each model. As mentioned above, the competing-risk model treats one event as censored while estimating another event's likelihood. Some future research in comparison between the two methodologies may improve our understanding of how to deal with such circumstances.

Table 6: Multi-nominal Logit Models of Delistings

Variable name	Delisting due to Merger and Acquisition		Delistings Due to Failure	
	Coefficient Estimate	Hazard Ratio	Coefficient Estimate	Hazard Ratio
Intercept	-1.1546**		-11.3592	
	[6.21]		[0.93]	
Venture dummy	0.0172	1.017	0.0197	1.02
	[0.06]		[0.03]	
Underpricing	0.0013***	1.001	0.0005	1.001
	[9.34]		[1.04]	
Proceeds	0.0002**	1.000	0.0005*	1.000
	[3.99]		[2.89]	
IPO activity	0.0018*	1.002	0.0052***	1.005
	[3.53]		[12.81]	
Firm age	-0.0042***	0.996	-0.0079***	0.992
	[7.01]		[9.32]	
Firm size	-0.2273***	0.797	-0.6557***	0.519
	[54.89]		[219.52]	
Profitability	0.0052***	1.005	-0.0137***	0.986
	[11.12]		[120.21]	
Growth	0.0005***	1.001	0.0008***	1.001
	[13.78]		[11.19]	
R&D expense	0.056**	1.058	-0.1325***	0.876
	[5.03]		[8.22]	
SGA expenses	0.1542***	1.167	0.1666***	1.181
	[15.89]		[9.99]	
Leverage	0.0019	1.002	0.0253***	1.026
	[1.71]		[178.37]	
IPO Year (80-89)	-1.2349***		8.4805	
	[8.00]		[0.00]	
IPO Year (90-99)	-1.398***		8.5230	
	[9.19]		[0.00]	
IPO Year (00-09)	-0.4413***		8.3506	
	[9.95]		[0.01]	
IPO Year (10-19)	-0.6571		9.2293	
	[2.07]		[0.00]	
IPO Year (20-21)	-1.2959***		8.7663	
	[7.97]		[0.00]	

Note: This table shows the results of a multinomial logit model on our sample as an additional test. The model is defined as

$$Logit(P_i) = \alpha_i + \beta_i X_i$$

The dependent variable is the log odds of delisting due to reason i, including (1) acquisition/merger and (2) failure. The independent variables are defined as follows. A venture dummy is defined as one if the IPO is backed by a venture firm, zero otherwise. Underpricing is defined as the initial return on the first trading day after going public. Proceeds is computed as Ln(1+Proceeds from the IPO in million dollars). IPO activity is measured using the number of IPOs per quarter. Age is calculated as Ln(1+Firm Age in years). Firm size is calculated as (1+Ln(MV)), where MV refers to the market value of common shares outstanding. Profitability is defined as net income divided by total assets. Growth is defined as a percentage change in total assets, calculated as (Total Assets$_t$ - Total Assets$_{t-1}$)/ Total Assets$_{t-1}$. R&D expenses is computed as research and development expenses divided by total assets. SGA expenses is computed as the selling, general, and administrative expenses divided by total assets. Leverage is computed as total liabilities divided by total assets. *, **, ***, significant at the 10, 5, and 1 percent level, respectively.

5.4 Time-varying covariates within the years after IPO

In this section, we like to examine the time-series patterns of those time-varying factors within the first five years after going public. In this table, we classify the observations of delisted IPOs into four groups, including (1) the observations at least one year earlier than the delisting year due to acquisition/merger, (2) the delisting year due to acquisition/merger, (3) the observations at least one year earlier than the delisting year due to failure, and (4) the delisting year due to failure. Each group is compared to the surviving IPO firms which have been listed on the public markets for the same period. Viewing the difference between surviving and delisted IPO firms across post-IPO stages provides deeper insight into what happened to the firms around the delisting events due to specific events. The results are reported in Table 7 as follows.

Table 7: Time-series Pattern of Covariates

	Delisting due to Merger and Acquisition							Delistings Due to Failure					
Time after IPO	Group 1: Surviving IPO	Group 2: Years before Delisting Year	Diff. between (2) vs (1)		Group 3: Delisting Year	Diff. between (3) vs (1)		Group 3: Years before Delisting Year	Diff. between (3) vs (1)		Group 4: Delisting Year	Diff. between (4) vs (1)	
Panel A: Profitability													
1	-1.301	-0.882	0.419		-5.655	-4.354	***	-10.653	-9.351	***	-35.784	-34.48	***
2	-4.644	-2.805	1.839	*	-11.436	-6.792	***	-18.056	-13.41	***	-58.562	-53.92	***
3	-5.706	-6.112	-0.41		-9.554	-3.848	**	-22.29	-16.59	***	-56.874	-51.17	***
4	-5.044	-5.231	-0.19		-13.521	-8.477	***	-18.465	-13.42	***	-52.977	-47.93	***
5	-3.912	-3.769	0.143		-10.077	-6.165	***	-18.093	-14.18	***	-48.244	-44.33	***
Panel B: Leverage													
1	37.126	35.653	-1.47	*	41.918	4.792	***	38.89	1.765	*	46.233	9.108	***
2	39.278	38.465	-0.81		40.8	1.522		47.774	8.496	***	59.795	20.52	***
3	40.765	40.91	0.145		43.097	2.332		51.807	11.04	***	79.323	38.56	***
4	43.053	42.45	-0.6		44.674	1.621		53.839	10.79	***	83.309	40.26	***
5	44.058	43.328	-0.73		45.781	1.723		54.453	10.4	***	84.672	40.61	***
Panel C: Firm Size													
1	12.395	11.743	-0.65	***	11.947	-0.448	***	11.068	-1.327	***	10.587	-1.808	***
2	12.339	11.65	-0.69	***	11.531	-0.808	***	10.694	-1.646	***	9.966	-2.374	***
3	12.335	11.586	-0.75	***	11.734	-0.601	**	10.48	-1.855	***	9.356	-2.979	***
4	12.39	11.62	-0.77	***	11.416	-0.974	***	10.49	-1.899	***	8.837	-3.553	***
5	12.473	11.645	-0.83	***	11.541	-0.932	***	10.427	-2.046	***	9.202	-3.271	***
Panel D: Growth													
2	196.4	159.5	-36.9	**	173	-23.4		109.8	-86.6	***	75.898	-120.5	***
3	30.47	29.507	-0.96		29.092	-1.378		15.282	-15.19	***	-11.078	-41.55	***
4	22.262	23.586	1.323		9	-13.26	***	12.077	-10.19	***	-3.678	-25.94	***
5	21.01	26.182	5.172	*	10.211	-10.8	***	9.485	-11.53	***	-17.14	-38.15	***
Panel E: R&D Expenses													
1	6.339	5.991	-0.35		5.365	-0.975		5.303	-1.037	**	4.427	-1.913	
2	8.232	7.368	-0.86	*	7.63	-0.602		7.593	-0.639		9.059	0.827	
3	8.233	8.127	-0.11		8.084	-0.149		8.46	0.227		9.353	1.12	
4	8.125	8.207	0.081		9.778	1.653	*	8.154	0.029		9.45	1.325	
5	7.685	7.596	-0.09		10.085	2.4	***	8.042	0.357		12.109	4.425	***
6	7.723	7.41	-0.31		7.743	0.02		8.219	0.496		9.292	1.569	
Panel F: SGA Expenses													
1	26.362	29.279	2.917	***	33.166	6.804	***	30.056		***	40.624	14.26	***
2	29.333	32.247	2.915	***	36.019	6.687	***	35.907		***	52.985	23.65	***
3	29.632	34.548	4.916	***	34.346	4.714	***	39.26		***	45.429	15.8	***
4	29.327	35.456	6.129	***	37.336	8.009	***	38.71		***	52.665	23.34	***
5	29.29	35.26	5.97	***	40.433	11.14	***	39.566		***	50.453	21.16	***
6	29.571	35.099	5.528	***	36.698	7.128	***	41.67		***	49.691	20.12	***

*Note: This table shows the time-series means of time-varying factors within the first five years after IPOs. Here, we classify the observations of delisted IPOs to four groups (Groups 2-5), including (1) the observations at least one year earlier than the delisting year due to merger&acquisition, (2) the delisting year due to merger&acquisition, (3) the observations at least one year earlier than the delisting year due to failure, and (4) the delisting year due to failure. Each group is compared to the surviving IPO firms (Group 1), which have been listed on the public markets for the same period. Profitability is defined as net income divided by total assets. Leverage is computed as total liabilities divided by total assets. Firm size is calculated as (1+ln(MV)), where MV refers to the market value of common shares outstanding. Growth is defined as percentage change in total assets, calculated as (Total Assets$_t$ -Total Assets$_{t-1}$)/ Total Assets$_{t-1}$. R&D expenses is computed as research and development expenses divided by total assets. SGA expenses is computed as the selling, general, and administrative expenses divided by total assets. *, **, ***, significant at the 10, 5, and 1 percent level, respectively.*

Panel A describes whether the profitability level of IPOs (computed as net income divided by total assets), which were delisted for either reason is significantly different from that of surviving IPOs. It is interesting to note that IPOs delisted due to acquisition/merger only underperformed the surviving counterparts until the last year before being delisted. Before the delisting year, there was no significant difference in profitability between the two groups during the first five years, with the exception of the second year. Such a pattern implies that the decision to exit the public markets through takeover events may be made only when the performance worsens compared to other new firms. Contrarily, the IPO firms which were delisted triggered by failure are found to underperform the surviving ones continuously since the first year after being public. It is consistent with Fama et al. (2004) that fundamentals play an important role in terms of default risk caused by failure.

Panel B shows the pattern of leverage as above. However, we find that leverage varies in a different way from profitability. There was no significant difference between these two groups through the post-IPO five-year period, including the delisting year due to merger/acquisition. It indicates that capital structure issues may not be considered in the decision to delist. On the other side, we find that IPO firms delisted due to failure have a higher leverage than surviving ones over a five-year period. Again, it seems that IPOs delisted due to failure have more debt than the surviving group since the first year after going public.

Another interesting result can be seen in Panel C, which summarises the pattern of firm size across groups. We find that firm size is significantly different between each group and the surviving group, implying that size effect on delisting is time-invariant.

In Panel D, growth has been shown to be significantly different only for the IPOs delisted due to failure. Such IPOs show a consistently slower growth rate than surviving ones.

Panel E indicates that expenditure and research expenses are not important issues to be considered regarding the delisting risk due to both events. On the other side, SG&A expenses show a similar pattern as firm size in Panel F; that is, such expenses may affect the delistings from the beginning of being public.

6. Conclusion

This paper investigates the impact of time-varying factors on the likelihood of delisting for two reasons, using one IPO panel data in the United States during 1980-2021. Doing so can allow us to identify the factors that can help more accurately predict delisting rates due to two primary events, merger and acquisition or liquidation and bankruptcy. In this paper, we perform a competing-risk analysis on a group of IPOs in the United States during the period of 1980-2021.

Following the extant literature, we include two groups of covariates in our analysis. The first is a set of IPO-deal characteristics, including venture-backed dummy, underpricing, IPO proceeds, and number of IPOs per quarter. The second group includes firm age, firm size, profitability, growth, research and development expenses, selling, general and administrative expenses, and leverage.

We find that including the aftermarket performance in a competing-risk model helps distinguish the impact of those covariates on the delistings caused by two events. For example, our result shows that profitability can increase the chance of IPO firms being delisted due to mergers and acquisitions, which decreases the chance of being delisted by liquidation and bankruptcy. In addition, our evidence indicates that time-varying covariates can impact the delistings in different ways. For instance, profitability is likely to cause delistings due to mergers and acquisitions only until the last year before the delisting year. In sum, our paper contributes to the literature by shedding new light on how to make accurate predictions of delisting rates.

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