APPLIED FINANCE LETTERS

VOLUME 10 * 2021

ARE STABLECOINS SAFE HAVENS FOR TRADITIONAL CRYPTOCURRENCIES? AN EMPIRICAL STUDY DURING THE COVID-19 PANDEMIC
Sang Baum Kang, Yao Xie, Jialin Zhao

FINANCIAL RISKS AND STOCK MARKET CRASHES: AN EMPIRICAL ANALYSIS OF THE TUNISIAN STOCK MARKET
Haifa Hammami,Younes Boujelbene

REVISITING GOLD'S SAFE HAVEN STATUS WITH THE UTILIZATION OF THE INDEX OF IMPLIED VOLATILITY AND THE VALUES OF EXCHANGE TRADED FUNDS
Dimitrios Panagiotou

DO ECONOMIC FORECASTERS BELIEVE THE STOCK MARKET IS EFFICIENT? EVIDENCE FROM GERMANY
Richard Deaves, Michael Schröder, Adam Stivers, Ming Tsang

IS BITCOIN IMMUNE TO THE COVID-19 PANDEMIC?
S. Thomas Kim, Svetlana Orlova

COVID-19 PANDEMIC AND HERDING BEHAVIOUR IN CRYPTOCURRENCY MARKET
Samuel Asante Gyamerah

INVESTOR ATTENTION AND HERDING IN THE CRYPTOCURRENCY MARKET DURING THE COVID-19 PANDEMIC
Hajam Abid Bashir, Dilip Kumar, K Shiljas

COVID-19 IS DEADLY! LONG LIVE THE KING, CORPORATE CASH HOLDINGS!
Akanksha Saxena, R. Ranajee, Ms Saumita Roy

RELATION BETWEEN NEGATIVE TONE IN NEWS RELEASES OF WHO AND INDUSTRY RETURNS DURING THE COVID-19 PANDEMIC
Denada Ibrushi, Helmi Jedidi

IMPACT OF COVID-19 ON CRYPTOCURRENCIES: EVIDENCE ON INFORMATION TRANSMISSION THROUGH ECONOMIC AND FINANCIAL MARKET SENTIMENTS
Irfan Haider Shakri, Jaime Yong, Erwei Xiang

PRESENCE OF ANALYSTS BEFORE IPO AND UNDERPRICING: A META-ANALYSIS
Udayan Karnatak, Chirag Malik

THE DAVIDS AND THE GOLIATHS: INVESTMENT DYNAMICS AND PERFORMANCE DIFFERENTIALS OF SMALL FIRMS AND FAMILY-CONTROLLED LARGE FIRMS IN FOUR SECTORS OF THE INDIAN MARKET
Jaideep Ghosh

AN ANOMALY WITHIN AN ANOMALY: THE HALLOWEEN EFFECT IN THE LONG-TERM REVERSAL ANOMALY
King Fuei Lee

COST OF EQUITY CAPITAL AND UNDERSTATED PENSION LIABILITIES
Huan Yang, Jun Cai, Lin Huang and Robert I. Webb

EDITORS
BART FRIJNS & ALIREZA TOURANI-RAD

Publishing in Applied Finance Letters

Applied Finance Letters publishes short empirical research with clear implications and relevance for the finance industry. The aim is to encourage discussions among academics, policy makers and financial practitioners.

For submissions please visit our website at https://ojs.aut.ac.nz/applied-finance-letters/index

Submitted articles go through a blind review process and may be returned to the authors for subsequent revision.

Please visit Applied Finance Letters for author's guidelines and style requirements.

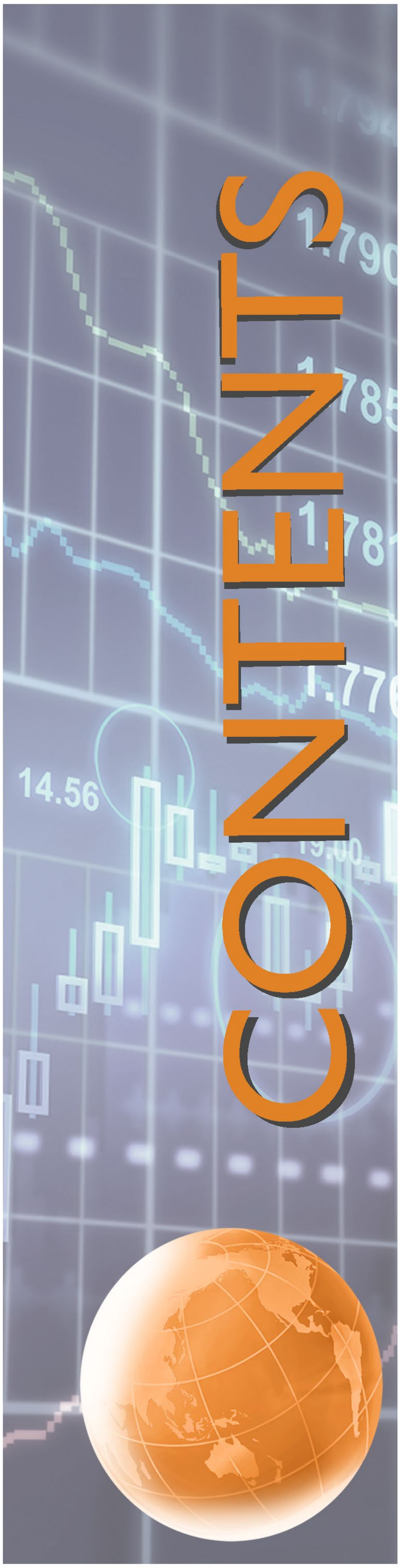
Copyright

ISSN 2253-5799 (Print)

ISSN 2253-5802 (Online)

APPLIED FINANCE LETTERS

VOLUME 10 * 2021



ARE STABLECOINS SAFE HAVENS FOR TRADITIONAL CRYPTOCURRENCIES? AN EMPIRICAL STUDY DURING THE COVID-19 PANDEMIC
Sang Baum Kang, Yao Xie, Jialin Zhao — Page 2

FINANCIAL RISKS AND STOCK MARKET CRASHES: AN EMPIRICAL ANALYSIS OF THE TUNISIAN STOCK MARKET
Haifa Hammami, Younes Boujelbene — Page 10

REVISITING GOLD'S SAFE HAVEN STATUS WITH THE UTILIZATION OF THE INDEX OF IMPLIED VOLATILITY AND THE VALUES OF EXCHANGE TRADED FUNDS
Dimitrios Panagiotou — Page 24

DO ECONOMIC FORECASTERS BELIEVE THE STOCK MARKET IS EFFICIENT? EVIDENCE FROM GERMANY
Richard Deaves, Michael Schröder, Adam Stivers, Ming Tsang — Page 40

IS BITCOIN IMMUNE TO THE COVID-19 PANDEMIC?
S. Thomas Kim, Svetlana Orlova — Page 48

COVID-19 PANDEMIC AND HERDING BEHAVIOUR IN CRYPTOCURRENCY MARKET
Samuel Asante Gyamerah — Page 58

INVESTOR ATTENTION AND HERDING IN THE CRYPTOCURRENCY MARKET DURING THE COVID-19 PANDEMIC
Hajam Abid Bashir, Dilip Kumar, K Shiljas — Page 67

COVID-19 IS DEADLY! LONG LIVE THE KING, CORPORATE CASH HOLDINGS!
Akanksha Saxena, R. Ranajee, Ms Saumita Roy — Page 78

RELATION BETWEEN NEGATIVE TONE IN NEWS RELEASES OF WHO AND INDUSTRY RETURNS DURING THE COVID-19 PANDEMIC
Denada Ibrushi and Helmi Jedidi — Page 93

IMPACT OF COVID-19 ON CRYPTOCURRENCIES: EVIDENCE ON INFORMATION TRANSMISSION THROUGH ECONOMIC AND FINANCIAL MARKET SENTIMENTS
Irfan Shakri,Jaime Yong, Erwei Xiang — Page 103

PRESENCE OF ANALYSTS BEFORE IPO AND UNDERPRICING: A META-ANALYSIS
Udayan Karnatak, Chirag Malik — Page 114

THE DAVIDS AND THE GOLIATHS: INVESTMENT DYNAMICS AND PERFORMANCE DIFFERENTIALS OF SMALL FIRMS AND FAMILY-CONTROLLED LARGE FIRMS IN FOUR SECTORS OF THE INDIAN MARKET
Jaideep Ghosh — Page 130

AN ANOMALY WITHIN AN ANOMALY: THE HALLOWEEN EFFECT IN THE LONG-TERM REVERSAL ANOMALY
King Fuei Lee — Page 151

COST OF EQUITY CAPITAL AND UNDERSTATED PENSION LIABILITIES
Huan Yang, Jun Cai, Lin Huang and Robert I. Webb — Page 160

APPLIED FINANCE LETTERS

VOLUME 10, 2021

ARE STABLECOINS SAFE HAVENS FOR TRADITIONAL CRYPTOCURRENCIES? AN EMPIRICAL STUDY DURING THE COVID-19 PANDEMIC

SANG BAUM KANG[1], YAO XIE[1*], JIALIN ZHAO[2]

1. Illinois Institute of Technology, 565 W Adams Street, Chicago, IL 60661, USA
2. St. Mary's University, 1 Camino Santa Maria, San Antonio, TX 78228

* Illinois Institute of Technology, 565 W Adams Street, Chicago, IL 60661, USA
yxie3@hawk.iit.edu

Abstract

We investigate whether stablecoins are safe havens for traditional cryptocurrencies with fresh evidence from the recent crisis period of the COVID-19 pandemic. Our results support the safe-haven properties of Tether for both before and during the pandemic. For Digix, a gold-backed stablecoin with relatively small market capitalization, we find a change in the characteristics before and during the pandemic, but do not find statistically significant evidence for its safe-haven properties. Furthermore, we document that, when considering the economic benefits and costs of adding safe-haven assets to cryptocurrency portfolios, the one with Tether outperforms both a naked portfolio and a portfolio with traditional safe-haven assets such as gold.

JEL Classification: G11, G15, G19

Keywords: Stablecoins; Safe-Haven Assets; COVID-19 Pandemic

1. Introduction

Innovative technologies such as blockchain have had profound impacts on society, financial markets included. The conceptualization of cryptocurrency and its technological implementations create a class of virtual assets that can bring disruptive developments to financial markets. Bitcoin, the most dominant cryptocurrency, has accumulated $200 billion in market capitalization as of 2020. Other cryptocurrencies have also drawn increasing attention from investors. Stablecoins, for instance, grew their market capitalization from $2.6 billion in 2019 to $20 billion in 2020, making a timely investigation into the characteristics of such an emerging crypto-asset relevant and important.

Stablecoins, backed by either fiat currencies or commodities, are designed to be price-stable cryptocurrencies (Mita et al., 2019; Sidorenko, 2020; Wei, 2018). Take Tether, a stablecoin pegged to USD with an anchor at $1, for example. Investors typically hold Tether to convert into other cryptocurrencies in the future – it currently accounts for more Bitcoin transactions than U.S. dollars (Griffin and Shams, 2020). As a result, it is not surprising to observe increasing interest from investors in stablecoins following the downturns of traditional cryptocurrencies. A stream of literature thus links the role of stablecoins to that of gold as hedges or safe-haven assets in cryptocurrency portfolios (Baur and Hoang, 2020; Wang et al., 2020).

Baur and Lucey (2010) define safe-haven assets as those with little or a negative correlation with other assets during crises. One of the widely recognized safe-haven assets is gold. During the 2007 – 2008 Financial Crisis, gold prices appreciated while other assets stumbled, effectively serving loss-averse investors. Expanding the existing literature on safe-haven assets is important, especially with the ongoing COVID-19 pandemic. With the first cases reported back at the close of 2019, COVID-19 quickly developed from a regional crisis to a global pandemic in early 2020, causing substantial losses in asset markets (Baker et al. 2020). For instance, Bitcoin lost $13 billion in market capitalization during the first quarter of 2020.

Facing such a severe crisis, can stablecoins function as effective and efficient safe-haven assets for traditional cryptocurrencies? Considering the linkage between traditional cryptocurrencies and stablecoins during December 2018 – July 2019, Baur and Hoang (2020) find the strongest safe-haven effects in Tether. Using data up to March 2019, Wang et al. (2020) also document the safe-haven property of stablecoins for traditional cryptocurrencies and note that such characteristics change across different market conditions. However, these empirical tests have been devoid of an essential component – a test during a period of significant turmoil in asset markets such as the recent COVID-19 pandemic.

Our paper fills such a gap by investigating the characteristics of stablecoins, both before and during a severe economic crisis. Our econometric model investigates how stablecoins such as the currency-based Tether and the gold-pegged Digix (DGX) react to extremely negative movements of Bitcoin during the COVID-19 pandemic period. We find that Tether consistently serves as a safe-haven asset for traditional cryptocurrencies, before and during the pandemic, whereas DGX does not. In addition, we analyse the risk-return trade-offs of cryptocurrency portfolios, including and excluding stablecoins. Our portfolio analysis aims to examine the effectiveness and efficiency of using stablecoins as safe-haven assets in traditional cryptocurrency portfolios. This paper adopts three evaluation measures: The Certainty Equivalent Return (Ferreira and Santa-Clara, 2011), the Expected Shortfall (Rockafellar and Uryasev, 2002), and the Economic Value of the Incremental Expected Shortfall (Kang, Ong, and Zhao, 2019). Considering Tether, DGX, and the traditional safe-haven asset of gold, we find that the portfolio with Tether has the highest performance.

Our contributions to the literature are threefold. First, this paper increases our understanding of the characteristics of an emerging financial asset – stablecoins. With a significant share of Bitcoin transactions denominated in Tether, studies on the relationship between traditional cryptocurrencies and stablecoins are increasingly relevant. Our paper builds upon the existing literature by adding an assessment of the safe-haven properties of stablecoins for traditional cryptocurrencies during a period of acute financial losses. Our empirical results show that Tether consistently exhibits safe-haven properties, before and during the COVID-19 pandemic, whereas DGX does not.

Second, our portfolio analysis indicates that adding stablecoins to a cryptocurrency portfolio results in an increased risk-adjusted return, compared to holding Bitcoin alone, with Tether outperforming both DGX and gold. Our findings have significant implications for investors searching for shelter from turbulence in the cryptocurrency markets.

Third, our paper joins and adds to a growing stream of literature investigating the impacts of the COVID-19 pandemic on financial markets. It is worth noting that the Sharpe ratio, arguably the most popular portfolio evaluation measure, does not capture the right preference order if the imputed values are in the negative spectrum[1]. Recognizing this limitation of the Sharpe ratio, we advocate the use of alternative portfolio performance measures during a period of potential acute financial losses such as the COVID-19 pandemic. This is another novelty that this paper introduces to related literature.

The rest of the paper is structured as follows. Section 2 introduces the data and methodology, Section 3 discusses the results, and Section 4 concludes.

[1] When a portfolio mean return is negative, the Sharpe ratio prefers a portfolio with a larger standard deviation to one with a smaller standard deviation. See Subsection 3.2 for details.

2. Data

We collect the prices of Bitcoin, USD-backed Tether, and gold-backed DGX, as denominated in U.S. dollars, at a two-hour interval from bitfinex.com during December 2018 – June 2020. The whole sample is further broken into two subsamples: pre-pandemic (December 2018 – December 2019) and pandemic (January 2020 to June 2020).

Table 1: Summary Statistics

	Pre-Pandemic				Pandemic			
	Bitcoin	Tether	DGX	Gold	Bitcoin	Tether	DGX	Gold
Observations	387	387	387	387	153	153	153	153
Mean	0.002	0.000	0.000	0.001	0.002	0.000	0.001	0.001
Standard Deviation	0.037	0.004	0.020	0.007	0.056	0.001	0.035	0.013
Skewness	0.232	-0.216	-1.751	0.158	-4.199	1.295	-0.312	-0.002
Kurtosis	3.321	6.144	35.404	1.190	37.660	22.788	1.850	2.384
Maximum	0.159	0.017	0.154	0.025	0.144	0.010	0.096	0.050
Minimum	-0.140	-0.021	-0.206	-0.022	-0.492	-0.008	-0.128	-0.037

This table presents the summary statistics of daily returns of Bitcoin, Tether, DGX, and gold. Pre-Pandemic is from December 2018 to December 2019, and Pandemic is from January 2020 to June 2020.

Although we use bi-hourly granularity in our empirical tests, we present the summary statistics of daily returns in Table 1 and correlations in Table 2 for an apples-to-apples comparison among Bitcoin, Tether, DGX, and gold. Compared with Bitcoin, stablecoins exhibit lower volatility for both before and during the pandemic. It is also worth noting that the co-movements between Tether and Bitcoin change from a weak direct relationship (correlation at 0.103) before the pandemic to a moderate inverse one (correlation at -0.557) during the pandemic.

Table 2: Return Correlations between Assets

Panel A: Pre-Pandemic				
	Bitcoin Return	**Tether Return**	**DGX Return**	**Gold Return**
Bitcoin Return	1.000	0.103	0.156	0.152
Tether Return	0.103	1.000	0.083	-0.041
DGX Return	0.156	0.083	1.000	0.213
Gold Return	0.152	-0.041	0.213	1.000

This table displays the return correlations before (Panel A) and during (Panel B) the pandemic period between Bitcoin, Tether, DGX, and gold. Pre-Pandemic is from December 2018 to December 2019, and Pandemic is from January 2020 to June 2020

3. Methodology and Results

3.1 Econometric Model

To investigate how stablecoins react to extreme movements in Bitcoin, we adapt the econometric model used by Baur and Hoang (2020):

$$r_{stablecoins} = \alpha_1 + \beta_1 r_{BTC} + \alpha_2 Q_{10\%} + \beta_2 r_{BTC} Q_{10\%} + \varepsilon \qquad (1)$$

where $r_{stablecoins}$ is the log return of stablecoins under consideration (i.e., Tether or DGX), r_{BTC} denotes the log return of Bitcoin, and the dummy variable $Q_{10\%}$ equals 1 if r_{BTC} is below the 10% quantile (i.e., extreme downward movements), and 0 otherwise.

If a stablecoin is immune to changes in the cryptocurrency markets, all βs are expected to be zero; if a stablecoin is subject to fluctuations in the cryptocurrency markets but do not react to extreme losses in particular, β_1 is expected to be non-zero, and β_2 is expected to be zero; and if a stablecoin serves as a safe-haven asset, β_2 is expected to be negative. It is also worth noting that if a stablecoin does not function as a "stable" asset but instead positively correlates with acute losses in the cryptocurrency markets, β_2 is expected to be positive.

Table 3: Regression Results

	Dependent Variable: Tether		**Dependent Variable: DGX**	
	Pre-Pandemic	**Pandemic**	**Pre-Pandemic**	**Pandemic**
$\boldsymbol{\beta_1}$	0.0884***	0.1118***	0.0954***	0.1703**
	(0.0121)	(0.0513)	(0.0148)	(0.0689)
$\boldsymbol{\alpha_1}$	0.0010	-0.0029***	0.0012	0.0036
	(0.0001)	(0.0043)	(0.0011)	(0.0041)
$\boldsymbol{\beta_2}$	-0.1262***	-0.1236***	0.1223***	-0.1198
	(0.0433)	(0.1263)	(0.0318)	(0.1231)
$\boldsymbol{\alpha_2}$	-0.0003**	-0.0002**	0.0001	-0.0001
	(0.0001)	(0.001)	(0.0001)	(0.001)
Observations	5654	1291	5654	1291
R^2	0.032	0.006	0.025	0.006
Adjusted R^2	0.031	0.005	0.025	0.004

This table shows OLS estimates for the regression model: r_stablecoins=a_1+β_1 r_BTC+a_2 Q_(10%)+β_2 〖r_BTC Q〗_(10%)+ε, where r_stablecoins is the log return of stablecoins under consideration (i.e., Tether or DGX), r_BTC denotes the log return of Bitcoin, and the dummy variable Q_(10%) equals 1 if r_BTC is below the 10% quantile (i.e., extreme downward movements), and 0 otherwise. Pre-Pandemic is from December 2018 to December 2019, and Pandemic is from January 2020 to June 2020. The standard error is reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

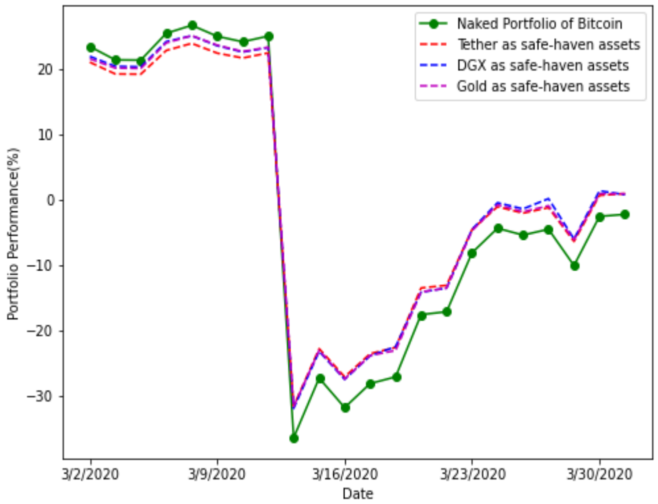
Table 3 shows our model estimation for Tether and DGX. The characteristics of Tether are relatively consistent, with statistically significant positive β_1s (0.0884 and 0.1118) and statistically significant negative β_2s (-0.1262 and -0.1236) in both the pre-pandemic and pandemic periods. The negative β_2s in both testing periods suggest that Tether consistently reacts negatively to extreme losses in Bitcoin, thereby supporting the safe-haven properties of Tether.

As to the gold-backed DGX, it reports a statistically significant positive β_2 (0.1223) before the COVID-19 pandemic and a negative β_2 (-0.1198) without significance during the pandemic. The pre-pandemic analysis finds that returns of DGX plummet, along with extreme downturns in Bitcoin. This observation indicates that DGX, a less-dominant stablecoin with a market capitalization of only 7 million, fails to function as a safe-haven asset in the pre-pandemic period. The negative β_2 (-0.1198) reported for the pandemic period indicates a somewhat promising inverse relationship between DGX and extreme losses in Bitcoin. However, such safe-haven properties of DGX do not show statistical significance.

3.2 Portfolio Analysis

In this subsection, we consider a portfolio worth $1 million with four possible asset allocations: 1) holding Bitcoin alone; 2) holding Bitcoin and Tether; 3) holding Bitcoin and DGX; and 4) holding Bitcoin and gold. For simplicity, we assume 90% and 10% weights for Bitcoin and the safe-haven position for this exercise. Figure 1 plots the performance of constructed portfolios in March 2020 when acute losses occurred. We find that portfolios with safe-haven assets navigate such severe losses much better than the naked portfolio.

Figure 1: Portfolio Performance



Note: This figure compares the performance of constructed portfolios in March 2020. The naked portfolio only consists of Bitcoin, with Tether, DGX, and gold introduced as safe-haven assets. For simplicity, Bitcoin and safe-haven asset positions are 90% and 10% in these portfolios.

In addition, we consider the risk-adjusted returns of cryptocurrency portfolios. It is worth noting that economic crisis periods such as the recent pandemic can easily be associated with negative asset returns. The use of classic evaluation measures requires additional caution during such a time. Take the Sharpe ratio, which is defined as $\frac{r_p - r_f}{\sigma_p}$, where r_f stands for the risk-free return, r_p for the portfolio return, and σ_p for the portfolio standard deviation. During a time of acute financial losses (i.e., $r_p - r_f < 0$), the imputed value of the Sharpe ratio falls into the negative spectrum, which can lead to a misleading interpretation. In Appendix A, we discuss the limitation of the Sharpe ratio in detail.

To address this concern, we use three alternative evaluation measures in this paper. The first one is the Certainty Equivalent Return (CER) (Ferreira and Santa-Clara, 2011). Stemming from the classic mean-variance framework, CER ($\equiv \bar{r_p} - \frac{\gamma}{2}\sigma_p{}^2$, where $\bar{r_p}$ is the expected portfolio return, σ_p is the portfolio standard deviation, and γ is the risk aversion parameter) is defined as the risk-free return that an investor with a risk aversion coefficient γ may consider as equivalent to investing in a particular portfolio.

The second measure is the Expected Shortfall (ES) (Rockafellar and Uryasev, 2002). With a pre-specified confidence level $(1-\alpha)$, ES estimates the average of the worst $100\alpha\%$ scenarios. Without requiring any artificial parameter, ES quantifies the fluctuations of portfolio values in an intuitive manner. However, such a measure does not fully capture the economic gains resulting from taking reasonable risks.

The third measure under consideration is the Economic Value of the Incremental Expected Shortfall (EVIES) (Kang, Ong, and Zhao, 2019), which allows us to evaluate the role of stablecoins from a cost-efficiency perspective. Building upon the fundamental principle of costs and benefits, EVIES was originally designed for corporations with hedging benefits captured in reinvesting the reduction in the capital reserve and hedging costs quantified by reduced cashflows. It is also worth noting that EVIES is mathematically proven to be monotonic, concave, and scale invariant, properties that guarantee stable hedging-effectiveness evaluations (Kang, Ong, and Zhao, 2019).

To implement EVIES in the context of cryptocurrency investment, we modify the original specifications of EVIES as the following: EVIES $\equiv r_{alternative} \times \Delta ES_{\alpha} - (1 - \tau_{income}) \times \Delta(Expected\ Revenue)$, where $r_{alternative}$ is the excess return of the alternative investment (estimated at 4%[2]), ΔES_{α} is the change in the Expected Shortfall after adding safe-haven assets to the naked portfolio, τ_{income} is the tax rate for the short-term capital gain (30%), and $\Delta(Expected\ Revenue)$ is the change in the expected return, compared to the naked portfolio.

Table 4 presents the imputed evaluation measures of CER, ES, and EVIES. In terms of CER, we observe that holding Bitcoin alone reports the lowest performance (3.48%). The risk-adjusted return can be improved by adding Tether (3.52%), DGX (3.51%), or gold (3.59%) to the portfolio. When measured in ES, the naked portfolio of Bitcoin reports the largest ES at $126,363, and the portfolio with Tether reports the smallest ES at $113,278. The mechanism of EVIES builds upon the comparison against a benchmark model – holding Bitcoin alone; thus, the benchmark portfolio does not report an imputed EVIES.

Table 4: Portfolio Analysis

Portfolio	(1) **CER**	(2) **ES ($)**	(3) **EVIES ($)**
Bitcoin	3.48%	-126,363	
Bitcoin + Tether	3.52%	-113,278	769.13
Bitcoin + DGX	3.51%	-113,671	723.65
Bitcoin + Gold	3.59%	-114,022	632.00

This table considers portfolios worth $1 million during the pandemic period. The first row represents the naked portfolio (which consists of Bitcoin), and the following rows represent portfolios with safe-haven assets such as Tether, DGX, and gold, respectively. For simplicity, Bitcoin and safe-haven asset positions are 90% and 10% in these portfolios. Column (1) reports the imputed Certainty Equivalent Return. Column (2) reports the Expected Shortfall, and Column (3) reports the Economic Value of Incremental Expected Shortfall.

Compared with this benchmark model, the portfolio with Tether reports the highest net economic value of $769.13, followed by DGX ($723.65) and gold ($632.00). Our empirical results suggest that adding safe-haven assets increases the risk-adjusted return relative to the naked cryptocurrency portfolio, with Tether delivering comparable and oftentimes superior performance than traditional safe-haven assets such as gold.

It is worth noting that we use 90% Bitcoin and 10% safe-haven assets in the portfolio analysis for simplicity and conservatism. In unreported tests (available upon request), we find that the portfolio with Tether overperforms other portfolios even more as the weight of safe-haven assets increases.

4. Conclusion

Stablecoins is a fast-growing sub-class of cryptocurrencies designed to offer price stability for cryptocurrency holders. This paper examines the role of stablecoins as safe-haven assets in traditional cryptocurrency portfolios with fresh evidence from the COVID-19 pandemic. By conducting both a regression-based econometric model and a portfolio analysis, we find that 1) Tether functions as a safe-haven asset in traditional cryptocurrency portfolios, before and during the COVID-19 pandemic, whereas the less-dominant gold-backed stablecoin DGX does not; 2) the

[2] Motivated by Constantinides et al. (2011)

characteristics of DGX change after the pandemic hit, whereas those of Tether do not; and 3) when measured using risk-adjusted measures, the cryptocurrency portfolio with Tether outperforms both the naked portfolio and the one using gold as a safe-haven asset. Recognizing the various characteristics of different stablecoins, this paper motivates future research concerning the heterogeneity of stablecoins.

References

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). COVID-induced economic uncertainty (No. w26983). National Bureau of Economic Research.

Baur, D. G., & Hoang, L. T. (2020). A crypto safe haven against Bitcoin. *Finance Research Letters*, 101431. https://doi.org/10.1016/j.frl.2020.101431

Baur, D.G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*. Vol. 45: 217-229.

Constantinides, G. M., Czerwonko, M., Carsten Jackwerth, J., & Perrakis, S. (2011). Are options on index futures profitable for risk-averse investors? Empirical evidence. *The Journal of Finance*, 66(4), 1407-1437.

Ferreira, M. A., & Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, *100*(3), 514–537. https://doi.org/10.1016/j.jfineco.2011.02.003

Griffin, J. M., & Shams, A. (2020). Is Bitcoin really untethered? *The Journal of Finance*, 75(4), 1913-1964.

Kang, S. B., Ong, M., & Zhao, J. (2019). A new approach to evaluating the cost-efficiency of complex hedging strategies: An application to electricity price–volume quanto contracts. *Journal of Energy Markets*, 12(3).

Mita, M., Ito, K., Ohsawa, S., & Tanaka, H. (2019, July). What is stablecoin?: A survey on price stabilization mechanisms for decentralized payment systems. In the 2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI) (pp. 60-66). IEEE.

Rockafellar, R. T., & Uryasev, S. (2002). *Conditional value-at-risk for general loss distributions*. 29.

Sidorenko, E. L. (2020). Stablecoin as a new financial instrument. In S. I. Ashmarina, M. Vochozka, & V. V. Mantulenko (Eds.), *Digital age: Chances, challenges and future* (Vol. 84, pp. 630–638). Springer International Publishing. https://doi.org/10.1007/978-3-030-27015-5_75

Wang, G.-J., Ma, X., & Wu, H. (2020). Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? *Research in International Business and Finance*, *54*, 101225. https://doi.org/10.1016/j.ribaf.2020.101225

Wei, W. C. (2018). The impact of Tether grants on Bitcoin. *Economics Letters*, *171*, 19–22. https://doi.org/10.1016/j.econlet.2018.07.001

Appendix A: Limit of the Sharpe Ratio

To illustrate the limits of the Sharpe ratio during the COVID-19 pandemic, we present two cases using four portfolios A, B, C, and D. The construct is presented in the following table.

	Case 1		**Case 2**	
	A	**B**	**C**	**D**
$r_p - r_f$	-10%	-10%	-10%	-5%
σ_p	5%	10%	5%	5%
Sharp Ratio	-2%	-1%	-2%	-1%

Let us consider the first case. With same expected return, A exhibits lower volatility, and thus should be preferred over B. In other words, a more negative figure of the Sharpe ratio implies better portfolio performance.

Let us consider the second case. With the same volatility, D exhibits a better return, and thus should be preferred over C. In other words, a less negative figure of the Sharpe ratio implies better portfolio performance.

This sample example sheds light on the inconsistency of the Sharpe ratio, which hinders its use during the COVID-19 pandemic.

Acknowledgements
We appreciate the detailed and constructive comments from an anonymous referee on an earlier version of the paper. We also thank Dr. Caroline Toscano for proof-reading our paper.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

FINANCIAL RISKS AND STOCK MARKET CRASHES: AN EMPIRICAL ANALYSIS OF THE TUNISIAN STOCK MARKET

HAIFA HAMMAMI[1]*, YOUNES BOUJELBENE[2]

1. Faculty of Economics and Management of Sfax, Department of Finance, Tunisia
2. Faculty of Economics and Management of Sfax, Department of Applied Economics, Tunisia

* Faculty of Economics and Management of Sfax, Department of Finance, Road of Aerodrome Km 4, 1013-3018 Sfax, Tunisia. ✉ haifa_hammami83@yahoo.fr

Abstract

This study aims to investigate the effect of financial risks on the stock market crash occurrence from 1999 to 2020. Using the windows method, we detect two stock market crises in the Tunisian stock market. Based on the probit model, we find evidence that low stock return risk, low EUR/TND exchange rate risk, high-interest rate risk, high credit risk and high liquidity risk increase the occurrence probability of stock market crashes. Our results suggest that the decrease in volatility, particularly in equity and exchange market, the increase in volatility in interest rate, the credit rating downgrades issued by Moody's and the low market liquidity contribute to crashes in the Tunisian stock market. In summary, financial risks, which are the market risks, the credit risk, and the liquidity risk, could be leading indicators of crashes in the Tunisian stock market.

Keywords: Stock market crashes; Liquidity risk; Credit risk; Market risks.

1. Introduction

Stock market crashes have been a topic of universal interest for both researchers and practitioners. Extensive literature in finance has concentrated on identifying the factors causing crises in the stock market. Previous studies conclude that financial and macro-economic indicators have played a significant role in causing stock market crashes (Mishkin, 1977; Fama, 1981; Reilly, 1997; Ottens et al., 2005; Coleman and Tettey, 2008; Khrawish et al., 2010; Berger and Pukthuanthong, 2012). Our framework differs from these empirical researches in that we analyse the effect of financial risks on stock market crises occurrence in addition to economic variables. Financial risks combine market risk, credit risk and liquidity risk.

The academic literature on stock market crises is well-established, starting with studies on liquidity risk by Geanakoplos (2003), Bernardo and Welch (2004), Brunnermeier and Pedersen (2009), Dick-Nielsen et al. (2012) and Fontaine et al. (2015), which conclude that high liquidity risk contributes to financial crises occurrence. Huang and Wang (2009) prove that the lack of liquidity supply decreases stock prices, leading to stock market crashes.

A rich literature on credit risk has also emerged. Janssen (2012) and Purnamasari et al. (2012) analyse the effect of credit risk on stock return. Other empirical studies concentrate on the interaction between market risk and stock return (Ryan and Worthington, 2004; Adjasi, 2006; Hyde, 2007; Mala and Reddy, 2007; Adjasi et al., 2011; Jawaid and Ul-Haq, 2012; Gulen and Ion, 2016).

Our main objective is to detect stock market crashes in the Tunisian stock market from 1999 to 2020 and empirically investigate the influence of financial risks on stock market crises.

The main contribution of our study is two-fold. First, our research is motivated by the insufficiency of empirical studies investigating the impact of financial risks: market risk, credit risk, and liquidity risk on stock market crash occurrences in emerging economies. Specifically, our analysis is a continuation of the initial surveys. It examines how financial risks explain stock market crises occurrence. Our research provides new empirical evidence by understanding the strong effects of market risk, credit risk and liquidity risk on stock market crises occurrence. Moreover, we extend the existing literature by presenting the key factors related to the emergence of stock market crises. Our paper provides a clear consensus on what causes a stock market crash and shows a significant relationship between financial risks and stock market crashes.

Second, our findings add new insights to investors and policymakers. In fact, investors need helpful information about market return, market liquidity, credit rating changes and currency market to make appropriate decisions when they buy or sell their stocks. Besides, understanding the strong effects of financial risks may lead policymakers to take appropriate measures to prevent the emergence of stock market crises.

Our paper is organised as follows: Section 2 outlines the literature relating stock market crises to financial risks and introduces the hypotheses. Section 3 presents the windows method used to identify stock market crises and the results obtained. Section 4 describes the methodology for modelling stock market crashes, the data and the measurement of financial risks and discusses our results. Section 5 concludes the empirical results.

2. Review of the literature and hypotheses

There is a great deal of interest in investigating the causes of stock market crashes occurrence. Financial theory focuses on financial risk as a critical factor of stock returns behaviour. Bhati and Sultan (2012) and Mehri (2015) suggest that financial risk influences stock returns. Kang and Kang (2009) and Aga et al. (2013) conclude that financial risks significantly affect stock returns. Berger and Pukthuanthong (2012) define their systemic risk measure the Fragility Index (FI) and find out that systemic risk is associated with the occurrence probability of international market crashes. They explain that a high level of systemic risk increases the emergence probability of a terrible market crash through various markets.

2.1 Relationship between market risk and stock market crashes

Some studies in the existing literature focus on the interaction between market risk and stock returns. Volatility in the equity market has become a mutual interest for investors and policymakers. Ryan and Worthington (2004) study bank stock return volatility using market risk, interest rate risk and foreign exchange risk over the 1996 - 2001 period. Their results indicate that market risk, short- and medium-term interest rate risk are the determinants of bank stock returns. Hyde (2007) documents that market risk significantly influences stock returns.

Officer (1973) proves that stock return volatility was at similar levels before and after the period of depression. Schwert (1989a) and Hamilton and Lin (1996) conclude that high stock market volatility is observed during a recession. Schwert (1989b) studies the stock return volatility around the 1987 crisis and shows higher market volatility during the crash and lower market volatility before the crisis of 1987.

Mala and Reddy (2007) find that high stock market volatility induces investors to demand a higher risk premium, increasing capital cost. Consequently, investment declines and economic growth slows down. Gulen and Ion (2016) put in evidence that the increase in stock return volatility has led to uncertainties in the policy. As a result, investment, output and employment decrease.

Adrian and Shin (2013) conclude that low stock return volatility leads financial institutions to take riskier positions and increase their balance sheet leverage, contributing to financial crises occurrence. Besides, financial intermediaries seek higher yields in low stock return volatility periods. As a consequence, they lend and reallocate from safer to riskier assets. In addition, Adrian and Shin (2013) prove that high stock return volatility could increase the financial crisis occurrence, as it reflects uncertainty about future cash flow.

Based on the current literature, we test the following hypothesis:
Hypothesis 1. Higher stock return risk increases the occurrence of stock market crises.

A considerable amount of research has been devoted to investigating the influence of exchange rate volatility on stock market crises occurrence. Branson (1983) and Frankel (1983) demonstrate that exchange rate volatility affects stock prices movements. They clarify that the exchange rate decrease encourages the investors to move funds from domestic stocks towards foreign stocks, declining stock prices. Khoo (1994) shows that stock returns are significantly related to exchange rate movements. Adjasi et al. (2011) analyse the impact of exchange rate movements on stock market returns in seven African countries. Their empirical findings indicate that in the long run, the drop-in exchange rate increases the stock market returns in some countries and in the short-run, the decrease in exchange rate reduces stock market returns.

Adjasi (2006) examines the effect of exchange rate volatility on stock returns during the 1951-2005 period. Its empirical evidence indicates that exchange rate volatility negatively affects stock returns. Sekmen (2011) studies the impact of exchange rate volatility on stock returns for the U.S. stock market from 1980 to 2008. The empirical analysis demonstrates that exchange rate volatility negatively influences U.S. stock returns.

Choi et al. (1992) investigate the relationship between exchange rate risk and stock returns. They find that stock returns are significantly related to exchange rate risk. Jawaid and Ul-Haq (2012) show that the effect of exchange rate risk on commercial banks stock returns is significant. However, Jorion (1991) and Bodnar and Gentry (1993) report an insignificant link between exchange rate risk and stock returns.

Hence the following hypothesis is presented:
Hypothesis 2. A rise in exchange rate risk increases the occurrence of stock market crashes.

Interest rate risk remains an important subject for researchers and regulators. Joseph and Vezos (2006) demonstrate that interest rate risk is a relevant financial factor affecting stock returns. Their empirical evidence shows that the stock returns are highly responsive to interest rate movements. Massomeh and Al Nasser (2017) analyse the link between interest rate volatility and stock market performance for 12 emerging economies over the period 1980-2011. The empirical evidence reveals a significant relationship between interest rate volatility and the stock market in the short-run for 12 emerging economies. However, their results indicate a significant link between the two variables only for 9 emerging economies in the long run. Banerjee and Adhikarys (2009) report an insignificant relationship between interest rate movements and the stock market return.

Based on the current literature, we investigate the following hypothesis:
Hypothesis 3. A rise in interest rate risk increases the occurrence of stock market crashes.

Interest rate is considered an important indicator that influences stock market returns. Mishkin (1977) points out that interest rate is negatively associated with stock returns. He explains that a low-interest rate induces higher capital flows to the stock market, increasing stock returns. However, a high-interest rate incites people to increase their savings in banks, thus decreasing the flow of capital to the stock market. Thorbecke (1997) suggests that a drop in interest rates encourages people to take out more loans at a lower cost of borrowing. As a result, an expansionary monetary policy seeks to amplify economic growth, increasing investment in the stock market. In addition, a decline in interest rate conducts investors to transfer their money from the bond market to the equity market. Other studies, such as Coleman and Tettey (2008) and Khrawish et al. (2010), prove that interest rates are negatively linked to stock market returns.

Hence the following hypothesis is tested:
Hypothesis 4. A high-interest rate increases the stock market crises occurrence.

2.2 Relationship between credit risk and stock market crises

Credit risk is one of the most important forms of financial risk that the stock market confronts. Naser et al. (2011) analyse the influence of credit and exchange rate risks on stock return volatility in Australia. Their results show a significant relationship between credit risk and exchange rate risk and stock return volatility. Janssen (2012) explores the influence of credit risk on stock returns from 2004 to 2012. The finding reveals that there is no significant link between excess returns on stocks and credit spreads. Purnamasari et al. (2012) find that credit risk is insignificantly related to stock returns.

While several empirical studies of credit risk have been concerned with credit rating changes and have analysed their impact on the stock market. The empirical evidence from Kaminsky and Schmukler (2002), Brooks et al. (2004), Martell (2005), Ferreira and Gama (2007), and Arezki et al. (2011) suggest that credit rating downgrades have a significant effect on the stock market and credit rating upgrades have limited effect. Hill and Faff (2010) find evidence that the reaction of financial markets to credit rating changes is more excessive during periods of crises. Afonso et al. (2012) study the effect of sovereign credit rating announcement on the stock market. They show that only negative credit rating signals have a significant impact on the stock market. Alsakka et al. (2017) suggest that the stock market reacts significantly to negative credit rating announcements issued by Standard and Poor's.

Based on the current literature, we postulate the following hypothesis:
Hypothesis 5. A rise in credit risk increases the occurrence of stock market crashes.

2.3 Relationship between liquidity risk and stock market crises

The relationship between liquidity risk and stock returns has been a subject of study for researchers over a long period. Gibson and Mougeot (2004) define market liquidity as the number of traded shares in the S&P 500 Index and show that stock returns are associated with the fluctuations in market liquidity. Moreover, they demonstrate that the October '87 Crash does not influence systematic liquidity risk. Huang and Wang (2009) demonstrate that the lack of liquidity supply negatively affects stock prices, causing stock market crashes.

Geanakoplos (2003), Bernardo and Welch (2004), and Brunnermeier and Pedersen (2009) provide evidence that high liquidity risk contributes to financial crises occurrence. Dick-Nielsen et al. (2012) demonstrate that a higher level of liquidity risk characterises the 2008 crisis. Fontaine et al. (2015) conclude that the decrease in stock returns is related to higher liquidity risk. Mehri (2015) studies the impact of financial risks on stock returns. The analysis sheds further light on the negative relationship between credit risk and capital risk on stock returns. However, the liquidity risk has an insignificant effect on stock returns.

Hence the following hypothesis is examined:

Hypothesis 6. A higher level of liquidity risk contributes to stock market crises occurrence.

2.4 Relationship between inflation and stock market crises

Fama (1981) shows a negative relationship between inflation and asset prices. Schwartz (1995) suggests that the higher inflation raises the inflation volatility and, therefore, the uncertainty. The uncertainty can increase the preference for safe assets. Reilly (1997) demonstrates that inflation is negatively related to stock prices. He explains that the increase in product costs induces firms to decrease their own selling prices. Consequently, the expected money flows reduce, thus decreasing stock prices.

Based on the current literature, we assume the following hypothesis:
Hypothesis 7. A rise in inflation increases the occurrence of stock market crises.

As stated above, we investigate the seven hypotheses to draw meaningful insights into the determinants of stock market crises occurrence.

3 Detecting stock market crises

The first step of our research consists of detecting stock market crises from January 1999 to February 2020. We use the windows method proposed by Mishkin and White (2002). These authors define a stock market crash as a decline of 20% in the stock market index over windows of one day, two days, five days, one month, three months and one year. The crashes of October 1929 and October 1987 are used as benchmarks to detect stock market crashes.

According to Mishkin and White (2002), we identify two stock market crashes for the TUNINDEX index from January 1999 to February 2020 using the twenty-four months window (see Table 1): the first crisis is from May 2001 to March 2003, and the second crisis is from September 2010 to May 2011. These stock market crashes are broadly consistent with the events occurring over the period.

Table 1: Detection of stock market crashes through the windows method

The crisis beginning	The trough date	The recovery date	Price decline to trough
May 2001	March 2003	4 years	-26.80 %
September 2010	May 2011	5 months	-24.75 %

Note: Table 1 defines the stock market crises that occurred during our sample period.

The first crisis occurred in May 2001 and reached a trough twenty-two months later in March 2003. It was characterised by a decrease of 26.8 per cent relative to the previous historical maximum level, but it took longer to recover about four years. The second stock market crisis of 2011 began in September 2010, and the TUNINDEX index decreased by 24.75 per cent relative to the previous historical maximum level.

4 Modelling stock market crashes

4.1 Methodology: A probit analysis of stock market crashes

The second step of our study consists of analysing the effect of financial risks on stock market crashes occurrence. To this end, we follow the probit model proposed by Kamnisky et al. (1997) to investigate the role of market risk, credit risk and liquidity risk in triggering stock market crises. In probit regression, the dependent variable is binary and can take only two values. The binary dependent variable called "a crisis indicator" equals to:

equals to: $I_t = \begin{cases} 1 \text{ for the crisis periods,} \\ 0 \text{ otherwise.} \end{cases}$

The probit model can be expressed as in (1):

$$\Pr(crisis_i = 1 | x_i, \beta) = 1 - \theta(-x'_i \beta) = \theta(x'_i \beta) \quad (1)$$

where θ represents the cumulative distribution of a standard normal random variable and x_i is the vector of explanatory variables for crises.

4.2 Data description and financial risks measurements

We use monthly data for the period beginning in January 1999 and ending in February 2020. Our data were obtained from the Central Bank of Tunisia, the Tunisian Stock Exchange and the National Institute of Statistics.

We define the measurements of the following financial risks.

Table 2: Moody's ratings and the numerical scale defined

	Rating	Scale
Investment	Aaa	20
	Aa1	19
	Aa2	18
	Aa3	17
	A1	16
	A2	15
	A3	14
	Baa1	13
	Baa2	12
	Baa3	11
Speculative	Ba1	20
	Ba2	19
	Ba3	18
	B1	17
	B2	16
	B3	15
	Caa1	14
	Caa2	13
	Caa3	12
	Ca	11
	C	2
	D	1
	WR	-

Note: In table 2, we convert the categorical scale (Aaa,..., C, D) of Moody's ratings into a numerical scale formed by 20 categories.

Credit risk: The proxy used to measure credit risk is the credit rating changes issued by Moody's. Following Williams et al. (2013) and Alsakka et al. (2014), we transform the categorical scale (Aaa,..., C, D) of Moody's ratings into a numerical scale formed by 20 categories as specified in table 2. We define an index that takes values from 1 to 20. The highest value is related to higher credit quality, thus a lower probability of default. This index, as developed by Hill and Faff (2010), is measured according to adding (subtracting) 0.5 points to the current rating, when a positive (negative) watchlist is issued or adding (substructing) 0.25 points when a positive (negative) outlook is published.

Liquidity risk: We define two proxies to measure liquidity risk. Based on Amihud (2002) empirical study, we include the first measure of liquidity, which is defined as the liquidity ratio of $\left|P_t - P_{t-1}\right| / V_t$. Where P_t is the monthly stock price index at the month t, P_{t-1} is the monthly stock price index at the month $t-1$ and V_t is the number of traded shares in TUNINDEX during a month.

The second liquidity measure used in this analysis is the Market Efficiency Coefficient (MEC) developed by Hasbrouck and Schwartz (1988).

$$MEC = \frac{Var(R_t)}{(n * Var(R_t / n))} \qquad (2)$$

Where $Var(R_t)$ is the variance of stock market return in the long period, $Var(R_t / n)$ is the variance of stock market return in a short period, and n is equal to the number of under periods by which we divided the long period. The Market Efficiency Coefficient (MEC), which is greater than 1, reflects a good level of liquidity, suggesting that short term stock market volatility is lower than its long-term stock market volatility. However, if the Market Efficiency Coefficient (MEC) is less than 1, stock market liquidity is low.

Interest rate risk: We incorporate interest rate volatility as a proxy of interest rate risk. The interest rate volatility is calculated as the standard deviation of 12 monthly interest rate.

EUR/TND exchange rate risk: To measure the EUR/TND exchange rate risk, we use the EUR/TND exchange rate volatility in this analysis equal to the standard deviation of 12 monthly exchange rate.

Tunindex index risk: We introduce Tunindex index volatility as a proxy of stock return risk. Tunindex index volatility is measured by calculating the standard deviation of 12 monthly Tunindex index.

We employ two control variables, such as inflation and interest rate. The inflation is calculated as $\left(\frac{CPI_t}{CPI_{t-12}} - 1\right) * 100$. The CPI_t is equal to the price index at the month t. Also, we use a monthly interest rate. The interest rate is equal to the Money Market Average (TMM).

The explanatory variables incorporated in the model are the Tunindex index volatility, the credit rating changes, the liquidity ratio, the Market Efficiency Coefficient (MEC), the EUR/TND exchange rate volatility, interest rate volatility, interest rate and inflation. These variables are introduced in the model in several stages to see if they could help investors estimate the occurrence probability of stock market crises.

4.3 Empirical results and discussion

We estimate our models on the full sample period from January 1999 to February 2020. The results of our regressions appear in table 3.

Table 3: Regression results on monthly sample

Models	(1)	(2)	(3)
Estimations Period		**1999 M1-2020 M2**	
Tunindex index volatility	-8.425218**	-7.889621*	-7.763519*
Credit rating changes	-0.888966***	-0.823819***	
Liquidity ratio	-43389.40***	-37748.93***	-39186.75***
Market Efficiency Coefficient (MEC)		-0.021525	-0.019197
EUR/TND exchange rate volatility			-16.34923**
Interest rate volatility		75.07187	220.9875***
Interest rate		56.94046***	27.34715*
Inflation			-42.82199***
Constant	9.949340***	6.139324**	-0.279030
R^2 Mc Fadden	0.433451	0.502777	0.426513
LR stat (p-value)	0.000000	0.000000	0.000000

Note: Table 3 presents the results of our regressions. In this table, (***), (**), (*) indicate that the test is significant at respectively 1%, 5%, and 10% level.

We construct three models that incorporate market, credit and liquidity risks in addition to the control variables.

We focus on detecting the presence of the endogeneity problem and robustness checks in our empirical analysis. First, we use the Likelihood Ratio test to control the endogeneity problem. As shown in table 3, we find the absence of the endogeneity problem based on the LR stat (p-value). Second, using a set of exhaustive robustness checks, we test the heteroskedasticity and the autocorrelation problems. One of the assumptions of the probit model, the sample is homoskedastic. In this case, we do not need to adjust for heteroskedasticity. As a result, there is no heteroskedasticity problem. For checking the autocorrelation problem, we use the correlogram of residuals. We put in evidence the absence of the autocorrelation problem. Thus, the deficiency of heteroskedasticity and autocorrelation problems suggests that our robust regression results still stand.

4.3.1 Results of Model (1)

To investigate the relative roles of financial risks in the occurrence probability of stock market crashes, the first empirical model incorporates Tunindex index volatility as a proxy of stock return risk, credit rating changes as a proxy of credit risk and liquidity ratio as a proxy of liquidity risk.

As shown in Table 3, higher tunindex index volatility is negatively and significantly related to the occurrence probability of stock market crises. In this sense, lower stock return volatility leads to the occurrence of crises in the Tunisian stock market. Our result implies that the low degree of stock market volatility induces investors to demand a higher risk premium, increasing the cost of capital. Consequently, investment declines, implying the decrease in stock prices. Besides, our result can be explained by the fact that a low risk in stock return encourages economic agents to take excessive risk in their investment, and thus, causes stock market crises.

Furthermore, low stock market volatility over a prolonged period induces higher risk-taking and leads to riskier investments. As a result, banks will support loan losses, causing a crisis in the stock market.

This result is consistent with the empirical evidence of Adrian and Shin (2013). Their findings reveal that low stock return volatility is positively and significantly related to financial crises occurrence. Conversely, the studies of Schwert (1989a and 1989b) and Hamilton and Lin (1996) seem contradictory to ours because, according to these authors, the high stock market volatility is observed during crises.

In addition, we notice that credit rating upgrades have a negative and significant impact on the occurrence probability of stock market crises. Therefore, this result supports the hypothesis that credit rating changes present relevant market information to investors. Hence, it is believed that agencies have access to private information. Consequently, credit rating downgrades issued by Moody's lead to the decrease in stock returns, causing crises in the stock market. This implies that investors perceive the credit rating downgrades as deterioration in the expectations of the cash flow. As a result, the investors react to credit rating changes and decrease their investment in periods of credit rating downgrades, causing stock market crises. Our result demonstrates that high credit risk is positively associated with the occurrence probability of crises in the stock market.

This result corroborates with the empirical results of Hill and Faff (2010) and Alsakka et al. (2017), who support the evidence that financial markets react significantly to credit rating changes during periods of crises. Besides, this result is consistent with the studies of Kaminsky and Schmukler (2002), Arezki et al. (2011) and Afonso et al. (2012), who suggest that credit rating downgrades have a significant effect on the stock market.

Furthermore, the liquidity ratio is negatively and significantly related to the occurrence probability of stock market crises. This result indicates that low market liquidity causes crises in the Tunisian stock market. Consequently, high liquidity risk contributes to a decrease in stock returns, triggering stock market crises. Our finding shows that an increase in liquidity risk leads to the occurrence of stock market crises. Our result is consistent with the empirical analyses of Geanakoplos (2003), Bernardo and Welch (2004), Brunnermeier and Pedersen (2009), Dick-Nielsen et al. (2012) and Fontaine et al. (2015), who conclude that high liquidity risk contributes to the occurrence of financial crises. Moreover, our analysis corroborates with the empirical evidence of Huang and Wang (2009), who underlines that the shortage of liquidity brings about the decrease in stock prices, which in turn causes stock market crashes.

In conclusion, it appears that low stock returns risk, high credit risk and high liquidity risk lead to stock market crashes occurrence.

4.3.2 Results of Model (2)

In model (2), we include, rather than the variables of model (1), a second proxy to liquidity risks, such as the Market Efficiency Coefficient (MEC), the interest rate volatility as a proxy of interest rate risk and the interest rate as a control variable. The results indicate that all explanatory variables are significant at 1%, 5% and 10% level, with the exception of the Market Efficiency Coefficient (MEC) and the interest rate volatility. The results obtained in model (2) can be summarised as follows. We conclude that low stock returns risk, high credit risk, high liquidity risk and high-interest rate increase the occurrence probability of stock market crises. Hence, stock return risk, credit risk and liquidity risk are found to be determinant in explaining stock market crises.

The empirical findings show that the interest rate has a positive and significant impact on the occurrence probability of stock market crises. This manifests that a high interest rate leads to a drop in stock returns, causing stock market crises. Our result is in accordance with the studies of Mishkin (1977), Thorbecke (1997), Coleman and Tettey (2008) and Khrawish et al. (2010), which demonstrate a significant negative relationship between interest rates and stock returns.

4.3.3 Results of Model (3)

The following model (3) is used to analyse whether market risk variables exert an impact on crashes occurrence probability. Market risk variables are stock returns risk, EUR/TND exchange rate risk and interest rate risk, and two proxies to measure liquidity risks, such as the liquidity ratio and the Market Efficiency Coefficient (MEC). The control variables correspond to the interest rate and inflation. As reported in Table 3, all market risk variables are significantly related to the occurrence probability of stock market crises. Our result shows that low stock return risk, low exchange rate risk and high interest rate risk are considered the key factors that lead to an increase in the occurrence probability of stock market crises.

As illustrated in Table 3, low exchange rate volatility exerts a positive and significant impact on the stock market crashes occurrence, suggesting that low EUR/TND exchange rate changes can affect the investors' wealth by generating losses based on the net foreign position. As a result, the investors' investment drops, decreasing stock returns and causing stock market crises. Besides, investors' perception of the future economic growth changes in a period of low exchange rate risk. They assume that the fluctuation of the exchange rate is fueled by economic instability, affecting the competitiveness of firms in the domestic stock market. Consequently, their profits will decrease, which in turn causes a decline in the domestic stock market. Besides, the investors tend to sell risky assets, including domestic currencies, which may trigger stock market crises.

We conclude that the exchange rate risk could be another important determinant of stock market crisis occurrence. Our results confirm the empirical evidence of Choi et al. (1992) and Jawaid and Ul-Haq (2012), which find that stock returns are significantly related to exchange rate risk and the empirical analyses of Branson (1983), Frankel (1983), Khoo (1994) and Adjasi et al. (2011) which show that stock returns are significantly related to exchange rate movements. However, our findings are inconsistent with the results of Adjasi (2006) and Sekmen (2011), which indicate that high exchange rate volatility negatively affects stock returns and with the analyses of Jorion (1991) and Bodnar and Gentry (1993), which report an insignificant link between exchange rate risk and stock returns.

Furthermore, our results reveal that both the interest rate and their volatility have a positive and significant effect on the occurrence probability of stock market crashes. In other words, high interest rate and high interest rate volatility are positively related to the stock market crises occurrence. Our findings suggest that high volatility in interest rate represents an important source of risk for investors' activity and can affect their investment. We conclude that large interest rate fluctuations reflect economic uncertainty; consequently, consumer spending and investment decline and borrowing becomes more difficult and expensive. As a result, stock prices drop, causing stock market crises.

One explanation for this latter result may be that an increase in interest rate decreases the present value of a firm's future cash flows, implying the drop in stock prices. Another explanation, a higher interest rate stimulates the capital inflow. Thereby, the exchange rate drops. As a result, stock returns decrease. Besides, the significant and positive effect can be interpreted as an increase in interest rates discourages people from taking out loans, decreasing investment in the stock market. In addition, a rise in interest rate leads people to transfer their money from the equity market to the bond market, implying the decline in stock prices.

Our results align with the empirical evidence of Joseph and Vezos (2006) and Massomeh and Al Nasser (2017), which highlight a significant effect of interest rate volatility on the stock market and show that interest rate risk is a relevant financial factor affecting the value of common stocks. Moreover, our findings corroborate with the results of Mishkin (1977), Thorbecke (1997), Coleman and Tettey (2008) and Khrawish et al. (2010), which demonstrate that interest rate is negatively related to the stock prices.

Besides, inflation is negatively and significantly related to the occurrence probability of stock market crises. Our result suggests that low inflation leads to a decrease in stock prices, causing stock market crises. Our empirical analysis reveals that despite the decrease in inflation, people anticipate a weaker expected economic activity and uncertainty about the future monetary policy, which increase the risk premium of the investors and thus, decrease asset prices. Our finding is inconsistent with Fama's (1981) and Reilly (1997) results, which suggest a negative relationship between inflation and asset prices.

5 Conclusion

The present study was conducted to identify Tunisian stock market crises and to examine their determinants, focusing on the financial risks. Firstly, we find that the Tunisian stock market crisis occurred in March 2003 and in May 2011 using the windows method.

Secondly, we combine market risk variables, such as stock return risk, EUR/TND exchange rate risk and interest rate risk, with the credit risk and the liquidity risk based on the probit model. The empirical findings of our study highlight that low stock return risk, low exchange rate risk, high interest rate risk, high credit risk and high liquidity risk lead to stock market crashes occurrence. In other words, the decrease in volatility, particularly in equity and exchange market, the increase in volatility in interest rate, the credit rating downgrades issued by Moody's and the low market liquidity contribute to crashes in the Tunisian stock market. In summary, financial risks, which are the market risk, the credit risk, and the liquidity risk, could be leading indicators of Tunisian stock market crises.

Our research has important implications for the literature focused on the causes of stock market crashes occurrence. Studying the effect of market risk, credit risk, and liquidity risk on the occurrence of stock market crises could provide helpful information to investors, academics and policymakers. Therefore, policymakers need to introduce appropriate measures and pursue policies to prevent the occurrence of stock market crashes.

Acknowledgements
We would like to thank Professors Najla Bouaziz and Khalil Mhadebi, the editor and two anonymous reviewers, for their many insightful and helpful comments and suggestions.

References

Adjasi, C.K.D., 2006. Are exporting firms really productive? Evidence from Ghana. African Journal of Business and Economics Research 2&3, 78-97.

Adjasi, C.K.D., Biekpe, B.N., Osei, K.A., 2011. Stock prices and exchange rate dynamics in selected African countries: a bivariate analysis. African Journal of Economic and Management Studies 2, 143-164.

Adrian, T., Shin, H.S., 2013. Procyclical leverage and Value-At-Risk. Working Paper No. 18943, National Bureau of Economic Research, 1-41.

Afonso, A., Furceri, D., Gomes, P., 2012. Sovereign credit ratings and financial markets linkages: application to European data. Journal of International Money and Finance 31, 606–638.

Aga, B.S., Mogadam, V.F., Samadiyan, B., 2013. Relationship between liquidity and stock returns in companies in Tehran stock exchange. Applied Mathematics and Engineering, Management and Technology 1, 278-285.

Alsakka, R., Gwilym, O., Nhung Vu, T., 2014. The sovereign-bank rating channel and rating agencies' downgrades during the European debt crisis. Journal of International Money and Finance 49, 235-257.

Alsakka, R., Gwilym, O., Vu, H., 2017. Differences of opinion in sovereign credit signals during the European crisis. European Journal of Finance 23, 1–26.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56.

Arezki, R., Candelon, B., Sy, A., 2011. Sovereign ratings news and financial markets spillovers: Evidence from the European debt crisis. IMF Working Paper, No. 11/68.

Banerjee, P.K., Adhikary, B.K., 2009. Dynamic effects of changes in interest rates and exchange rates on the stock market return in Bangladesh. Ritsumeikan Journal of Asia Pacific Studies 25, 119-133.

Berger, D., Pukthuanthong, K. 2012. Market fragility and international market crashes. Journal of Financial Economics, 105, 565-580.

Bernardo, A., Welch, I., 2004. Liquidity and financial market runs. Quarterly Journal of Economics 119, 135–158.

Bhati, V., Sultan, J., 2012. Leverage risk, financial crisis and stock returns: A comparison among islamic, conventional and social responsible stocks. Islamic Economic Studies 20, 87-143.

Bodnar, G.M., Gentry, W.M., 1993. Exchange rate exposure and industry characteristics: evidence from Canada, Japan, and the USA. Journal of International Money and Finance 12, 29-45.

Branson, W.H., 1983. Macroeconomic determinants of real exchange risk in managing foreign exchange risk, in: Herring, R.J., (ed.), Cambridge University Press, Cambridge MA.

Brooks, R., Faff, R., Hillier, D., Hillier, J., 2004. The national market impact of sovereign rating changes. Journal of Banking and Finance 28, 233–250.

Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. Review of Financial Studies 22, 2201–2238.

Choi, J.J., Elyasiani, E., Kopecky, K. J., 1992. The sensitivity of bank stock returns to market, interest and exchange rate risks. Journal of Banking and Finance 16, 983-1004.

Coleman, A. K., Tettey, K.F.A., 2008. Impact of macroeconomic indicators on stock market performance: The case of the Ghana stock exchange. Journal of Risk Finance 9, 365- 378.

Dick-Nielsen, J., Feldhutter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics 103, 471–492.

Fama, E., 1981. Stock returns, real activity, inflation, and money. American Economic Review 71, 545–565.

Ferreira, M., Gama, P., 2007. Does sovereign debt ratings news spill over to international stock markets? Journal of Banking and Finance 31, 3162–3182.

Fontaine, J.S., Garcia, R., Gungor, S., 2015. Funding liquidity, market liquidity and the cross-section of stock returns. Bank of Canada Working Paper, No. 2015-12, Bank of Canada, Ottawa.

Frankel, J.A., 1983. Monetary and portfolio balance models of exchange rate determination, in economic interdependence and flexible exchange rates, in: Bhandari, J.S., Putnam, B.H., (Eds.), Economic Interdependence and Flexible Exchange Rates, MIT Press, Cambridge MA, pp.84-115.

Geanakoplos, J., 2003. Liquidity, default and crashes: endogenous contracts in general equilibrium, in: Dewatripont, M., Hansen, L.P., Turnovsky, S.J. (Eds.), Advances in economics and econometrics: Theory and applications II, Econometric Society Monographs: Eighth World Congress, pp.170–205. Cambridge University Press, Cambridge.

Gibson, R., Mougeot, N., 2004. The pricing of systematic liquidity risk: Empirical evidence from the US stock market. Journal of Banking and Finance 28, 157-178.

Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. Review of Financial Studies 29, 523-564.

Hamilton, J.D., Lin, G., 1996. Stock market volatility and the business cycle. Journal of Applied Econometrics 11, 573–593.

Hasbrouck, J., Schwartz, R., 1988. Liquidity and execution costs in equity markets. Journal of Portfolio Management 14, 10-17.

Hill, P., Faff, R., 2010. The market impact of relative agency activity in the sovereign ratings market. Journal of Business Finance and Accounting 37, 1309-1347.

Huang, J., Wang, J., 2009. Liquidity and market crashes. The Review of Financial Studies, 22, 2607-2643.

Hyde, S., 2007. The response of industry stock returns to market, exchange rate and interest rate risks. Manchester Business School Working Paper, No. 9679, pp.1-20.

Janssen, L., 2012. The Effect of Credit Risk on Stock Returns, Tilburg University, Netherlands.

Jawaid, S.T., Ul-Haq, A., 2012. Effects of interest rate, exchange rate and their volatilities on stock prices: Evidence from banking industry of Pakistan. Theoretical and Applied Economics 19, 153-166.

Jorion, P., 1991. The pricing of exchange rate risk in the stock market. Journal of Financial and Quantitative Analysis 26, 363-376.

Joseph, N.A., Vezos, P., 2006. The sensitivity of US bank's stock returns to interest rate and exchange rate changes. Managerial Finance 32, 182-199.

Kaminsky, G., Lizondo, S., Reinhart, C.M., 1997. Leading indicators of currency crises. IMF Working Paper, No. 97/79, pp.1-43.

Kaminsky, G., Schmukler, S., 2002. Emerging market instability: do sovereign ratings affect country risk and stock returns? World Bank Economic Review 16, 171–195.

Kang, C., Kang, H.G., 2009. The effect of credit risk on stock returns. Journal of Economic Research 14, 49-67.

Khoo, A., 1994. Estimation of foreign exchange exposure: an application to mining companies in Australia. Journal of International Money and Finance 13, 342-363.

Khrawish, H.A., Siam, W.Z., Jaradat, M., 2010. The relationships between stock market capitalisation rate and interest rate: Evidence from Jordan. Business and Economic Horizons 2, 60-66.

Mala, R., Reddy, M., 2007. Measuring stock market volatility in an emerging Economy. International Research Journal of Finance and Economics 2007, 126-133.

Martell, R., 2005. The effect of sovereign credit rating changes on emerging stock markets. Working Paper, Purdue University.

Massomeh, H., Al Nasser, O.M., 2017. The impact of interest rate volatility on stock market development: Evidence from emerging markets. The journal of Developing Areas 51, 301-313.

Mehri, A.B., 2015. The effects of financial risks on the relationship between earnings and stock returns. International Journal of Organizational Leadership 4, 154-169.

Mishkin, F., 1977. What depressed the consumer? The household balance sheet and the 1973-1975 recession. Brookings Papers on Economic Activity 1, 123-164.

Mishkin, F., White, E., 2002. US Stock market crashes and their aftermath: Implications for monetary policy. NBER Working Papers, No. 8992.

Naser, S., Mohammad, E., Mohammad, R.H., Akbar, A.T., 2011. Designing and identifying the model to investigate the effect of credit and exchange risk on stock returns of banks (GARCH Approach). Australian Journal of Basic and Applied Sciences 5, 1519-1532.

Officer, R.R., 1973. The variability of the market factor of New York Stock Exchange. Journal of Business 46, 434-453.

Ottens, D., Lambregts, E., Poelhekke, S., 2005. Credit booms in emerging market economies: a recipe for banking crises? Working Paper, No. 046, De Nederlandsche Bank NV.

Purnamasari, K., Herdjiono, I., Setiawan, E., 2012. Financial risk, growth, earnings and stock returns relationship: The case of Indonesia. International Review of Business Research Papers 8, 79-93.

Reilly, F., 1997. The impact of inflation on roe, growth and stock prices. Financial Services Review 6, 1–17.

Ryan, S., Worthington, A., 2004. Market, interest rate and foreign exchange rate risk in Australian banking: A GARCH-M approach. International Journal of Applied Business and Economic Research 2, 81-103.

Schwartz, A., 1995. Why financial stability depends on price stability? Economic Affairs 15, 21–25.

Schwert, G.W., 1989a. Why does stock market volatility change over time? Journal of Finance 44, 1115-1153.

Schwert, G.W., 1989b. Stock volatility and the crash of 87. Working Paper, No. 2954, pp.1-32.

Sekmen, F., 2011. Exchange rate volatility and stock returns for the U.S. African Journal of Business Management 5, 9659-9664.

Thorbecke, W., 1997. On stock market returns and monetary policy. Journal of Finance 52, 635-654.

Williams, J., Calice, G., Chen, J., 2013. Liquidity spillovers in sovereign bond and CDS markets: An analysis of the Eurozone sovereign debt crisis.

Journal of Economic Behavior and Organization 85, 122-143.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

REVISITING GOLD'S SAFE HAVEN STATUS WITH THE UTILIZATION OF THE INDEX OF IMPLIED VOLATILITY AND THE VALUES OF EXCHANGE TRADED FUNDS

DIMITRIOS PANAGIOTOU[1*]

1. University of Ioannina, Ioannina, Greece

* Corresponding Author: Dimitrios Panagiotou, Department of Economics, University of Ioannina, Ioannina, Greece ✉ dpanag@uoi.gr

Abstract

The coronavirus pandemic is a health and economic crisis which has placed an immense strain on the world's financial system. Hence, amidst the (still ongoing) Covid-19 pandemic, the objective of this work is to investigate the role of gold as as a hedge or safe haven with the use of exchange traded funds. The present work employs the implied volatility index of gold share options (GVZ), the net asset value of the price per share of the US Oil Fund options (USO) and the value of the Currency Share Euro Trust (FXE). The statistical tool utilized is the quantile regressions methodology. Data are daily observations from June 2008 to May 2021. The empirical results reveal that gold's implied volatility decreases significantly (or it is not statistically different than zero), under changes in the average returns and/or under extreme market declines in FXE and USO. According to the aforementioned findings, gold could be an investment vehicle to serve as a hedge and or a safe haven asset. The present study is the first one to employ quantile regressions (QR) along with gold's implied volatility and the prices of exchange traded funds (ETFs) in order to investigate gold's hedge and/or safe haven properties.

1. Introduction

The coronavirus pandemic is a health and economic crisis which has placed an immense strain on the world's financial system. Amid the spread of Covid-19 around the globe, stock and bond markets worldwide have experienced significant losses and unprecedented volatility. As an example, on March 9th, 2020, Brent crude oil prices collapsed, falling by as much as 31\%, which was the largest single-day drop since the U.S. invaded Iraq in 1991. Figures 1 and 2 present the evolution of oil prices and the euro/dollar (EUR/USD) exchange rates, for the month of March, where the pandemic have had the biggest impact around the globe. Between March 6th and March 20th, oil prices fell by almost 50%.[1] For the same time period, the EUR/USD exchange rate fell by almost 7%, then increased by 5%, and fell again by the same percentage points.

According to the leverage hypothesis expressed by Christie (1982), a negative return in the value of the stock increases the financial leverage, making this way the stock riskier and as a

[1] Crude oil was hit really hard: a price war between Saudi Arabia and Russia caused prices to plunge, and energy prices typically decline when economic activity slows down.

result the underlying volatility increases. While major banks were heavily fortified after the financial crisis in 2008, stock and bond markets have shown signs of turbulence as investors get rid of anything with a hint of risk. The key question is, which investment(s) serve as a hedge or safe haven in periods of uncertainty and extreme stock market volatility.

In the finance literature, gold has been found to act both as a hedge as well as a safe haven asset Anand and Madhogaria, 2012; Baur and Lucey, 2010; Beckmann et al., 2015; Reboredo and Rivera-Castro, 2014).[2] Gold is known to be frequently uncorrelated with other assets (Baur and Lucey, 2010) and is said to be a zero-beta asset (Mccown and Zimmerman, 2006). Accordingly, gold seems to be appropriate to be considered as a hedge and/or a safe haven for financial assets or portfolios. The reason is that, in contrast to many other commodities, gold is known to be durable, easily recognizable, storable, portable, divisible, and easily standardized (Baur and McDermott, 2010).

Figure 1: WTI Crude oil prices (source: Oilprice.com)

The main objective of this work is to revisit gold's safe haven and/or hedge properties - against movements in the oil prices as well as against the EUR/USD exchange rate - with the utilization of the implied volatility of gold shares options along with the values of the exchange traded funds (ETFs) of oil and EUR/USD. In doing so, it employs the econometric tool of the parametric quantile regressions (QR). QR modelling provides more flexibility and presents significant advantages over existing methodologies. The main advantages are:

i. QR can capture a possible non-linear relationship between the dependent and the independent variable, even though the estimated regression function is linear at a given quantile,
ii. QR do not require any specific assumptions about the error distribution.

Accordingly, the quantile regressions approach is robust to non-normal errors and to outliers, and

iii. the derived QR estimator is asymptotically normal, it has an analytical variance-covariance estimator and it is invariant to monotonic transformations of the data.

[2] On the 25th of February of 2020, stock markets around the world presented significant losses and gold prices climbed to levels not seen since February 2013, the price of gold ascended to its highest level in seven years, as worries about the coronavirus led investors to seek a safe place for their capital.

Figure 2: Euro/dollar exchange rate (source: Exchangerates.org.uk)

Worldwide, gold and oil are major commodities and their price movements have important implications for the real economy as well as the financial markets. Gold and oil prices may drive the prices of other commodities (Sari et al., 2010) and can often act as an indicator of the health of the economy. In times of a financial crisis or high rates of inflation, many investors turn to gold in order to "seek for shelter". On the other hand, in periods of economic stability, investors are more likely to turn to more speculative investments, such as stocks, bonds and real estate. Concurrently, significant oil price hikes have been blamed for economic recessions, trade deficits, high inflation, high investment uncertainty and low stock and bond values. The value of crude oil stocks may have far broader implications with regard to financial stability and to macroeconomic performance (Fousekis, 2019).

Gold has been tested to have safe haven as well as hedge properties against oil price movements. Ciner et al. (2013) used daily data between January 1990 to June 2010, for the US and the UK, in order to investigate how and under what circumstances each of the five major financial assets, stocks, bonds, oil, gold, and the US dollar, provide a hedge or a safe haven function to each other. The authors detected that gold acts as a safe haven for most assets, except of oil. Baffes (2007) examined the pass-through of crude oil price changes to the price of thirty-five internationally traded primary commodities. The findings indicated that the price of precious metals, and in particular gold, responded strongly to the crude oil price. Hammoudeh and Yuan (2008) employed volatility models, from the generalized autoregressive conditional heteroskedasticity (GARCH) family, in order to study the impact of oil prices on gold returns and the volatility of gold returns. The EGARCH model (exponential general autoregressive conditional heteroskedastic), revealed that oil price shocks had an insignificant effect on gold returns. On the other hand, oil price shocks significantly reduced the volatility of gold returns. Soytas et al. (2009) studied the relationship between oil prices and gold, silver and other macroeconomic variables for the case of Turkey. A vector autoregressive model used in order to examine the short-run and long-run relationships between metal prices and the price of oil. Based on daily data, they reported that the world oil price had no predictive power over precious metal prices, such as gold. Narayan et al. (2010) examined the long-term relationship between gold and oil prices, both spot and futures, at different maturities. The findings revealed that investors used gold as a hedge against inflation and that oil and gold could be used to mutually predict prices. Using daily data, Zhang and Wei (2010) studied the cointegration relationship, linear and non-linear Granger causality and price discovery for crude oil and gold markets. Their evidence suggested that: i) crude oil and gold markets shared similar price trends, ii) there was a long-term equilibrium relationship between the two markets, iii) there was linear Granger causality from the oil price to the gold price but not vice versa and, iv) there was no evidence of non-linear Granger causality. Sari et al. (2010) employed impulse response functions and forecast error variance decompositions in order to analyse the effect of oil price shocks on precious metal returns and the US dollar/euro exchange rate. The empirical evidence indicated that precious metal markets responded positively and significantly to oil prices, but only in the short-run, with the effect dissipating over the long-run. Reboredo (2013a) assessed the role of gold as a hedge and/or safe haven against oil price movements. The author employed a testing approach based on using copulas. Empirical findings indicated that gold cannot hedge against oil price movements but it can act as an effective safe haven against extreme oil price movements.

The relationship between changes in the price of gold and the US dollar (USD) has also been investigated in the literature. Capie et al. (2005) assessed the role of gold as a hedge against the US dollar by estimating elasticities for a model of the responsiveness of gold to changes in the exchange rate. Capie confirmed the positive relationship between USD depreciation and the price of gold, making gold an effective hedge against the USD. Sjaastad (2008) found that currency appreciations or depreciations had strong effects on the price of gold. Joy (2011) analysed whether gold could serve as a hedge or an investment safe haven with the use of multivariate GARCH model of dynamic conditional correlations. The empirical results suggested that gold has been an effective hedge but a poor safe haven against the USD. Baur and McDermott (2010) found that gold and the US dollar act as safe haven assets during periods of market stress. Reboredo (2013c) assessed the role of gold as a safe haven or hedge against the US dollar (USD) using copulas to evaluate average and extreme market dependence between gold and the USD. The empirical evidence revealed positive and significant average dependence between gold and USD depreciation which is consistent with the fact that gold can act as a hedge against USD rate movements. Furthermore, the findings suggested symmetric tail dependence between gold and USD exchange rates, indicating that gold can act as a safe haven against extreme USD rate movements. This paper contributes in two ways to the existing literature on gold as a hedge and/or safe haven against currency depreciation. The strength of gold's safe haven effect is most clearly illustrated in specific crisis episodes where the reaction of gold is more pronounced than that of other potential safe haven assets.

All of the aforementioned studies, as well as the relevant literature in finance, utilize the price of gold and the price of oil as well as the USD exchange rate, in order to test gold's safe haven and/or hedge status against the aforementioned assets. Hence, despite the fact that the abovementioned channels well establish the safe haven and/or hedge status of gold and its use for portfolio diversification, no study to date has analysed the co-movement of gold prices against oil prices and the USD exchange rate with the employment of gold's implied volatility index.

Against this background, the objective of this work is to revisit the subject and and draw inferences on gold's investment status (hedge and/or safe haven) with the employment of daily prices of the US Oil exchange traded fund (USO), the EUR/USD exchange traded fund (FXE) and the implied volatility index of gold (GVZ), as produced by the Chicago Board Options Exchange (CBOE)[3].

To the best of our knowledge, this is the first study to employ gold's implied volatility and the prices of exchange traded funds in order to investigate gold's hedge and/or safe haven properties. The index of implied volatility reflects the market expectations for the future volatility of the underlying equity index. Implied volatility is often referred as the investors' fear

[3] The results make a timely contribution as during the writing of this manuscript financial markets around the globe are experiencing unprecedented volatility and declining returns due to the economic problems stemming from the coronavirus pandemic.

gauge. Fear and uncertainty largely drive the volatility. As fear and uncertainty grow bigger, the index of implied volatility gets higher.

The contribution of this article to the existing literature is threefold: i) it uses of the implied volatility of gold in order to test gold's ability to act as a financial safe haven and/or a hedge, ii) it employs exchange traded funds, namely the USO (oil price) and the FXE (US dollar/Euro exchange rate), and iii) it utilizes the QR approach as the econometric tool in order to draw inferences about financial safe havens and hedges.

In the era of globalization, correlations among most types of assets has increased dramatically, leading this way to increased price and variation volatility (Beckmann et al., 2015). As a consequence, investors seek out to diversify their portfolio and include investments that will act as a safe haven during times of crisis. The latter is extremely useful for portfolio managers who want to maintain a diversified portfolio and who want investment protection against downside risk. Gold, is known to be frequently uncorrelated with other assets (Bredin et al., 2017; Hood and Malik, 2013). Based on the empirical findings, this study makes inferences about gold's safe haven properties in the global financial system. The latter is extremely useful for portfolio managers who want to maintain a diversified portfolio and who want investment protection against downside risk. In addition, it is useful for policy makers, given the association between gold and macroeconomic variables, such as interest rates and exchange rates (Reboredo, 2013b; Soytas et al., 2009).

In what follows section 2 presents the analytical framework, section 3 the data and section 4 the empirical models and results. Section 5 offers conclusions and suggestions for future research.

2. Quantile Regressions Methodology

The quantile regressions (QR) can potentially describe the entire conditional distribution of the response. QR measure the marginal effects of explanatory variables by estimating regression coefficients and they express the marginal effects of the explanatory variable on the explained variable in a specific quantile. Therefore, quantile regressions make it possible to analyze the levels of the impact of the explanatory variable on the explained variable in different quantiles.

QR can be viewed as a generation of OLS to a collection of models with different conditional quantile functions. The ordinary least squares (OLS) estimates minimize $\sum_i e_i^2$, the sum of the squared error terms and they enable us to estimate models for conditional mean functions. Comparatively quantile regression minimize a weighted sum of the positive and negative error terms that gives asymmetric penalties $(1\text{-}q)|ei|$ for over-prediction and $q|ei|$ for under-prediction. If the quantile q differs from 0.5, there is an asymmetric penalty, with increasing asymmetry as q approaches 0 or 1.

Quantile regressions do not assume a particular parametric distribution for the response, nor do they assume a constant variance for the response, unlike OLS regression. Although its computation requires linear programming methods, the quantile regression estimator is asymptotically normally distributed.

The quantile regression model (Koenker and Bassett Jr, 1978; Koenker and Hallock, 2001) offers considerable flexibility in empirical research since it disposes with the common slope assumption, by allowing the effect of a change in the independent variable to vary along the conditional distribution of the dependent variable. Hence, quantile regression approach estimates the relationship between the independent variable and the dependent variable in different quantiles in order to have a complete picture of the overall distribution.

In the quantile regression approach the t sample quantile can be obtained by solving the following minimization problem:

$$\hat{q}_\tau = \arg\min_{q \in R^k} \sum_{i=1}^{N} \rho_\tau(Y_i - q) \quad (1)$$

where $0 < \tau < 1$, ρ_τ is the tilted absolute value function and $k = dim(\beta_q)$. Now, let's assume that the conditional τ-quantile function is $Q_{Y|X}(\tau) = X\beta_\tau$. Given a sample of observations (Y_i, X_i) with i=1,2,...N as well as the distribution function of Y, the estimated value of β_τ can be obtained by solving:

$$\hat{\beta}_\tau = \arg\min_{\beta_\tau \in R^k} \sum_{i=1}^{N} \rho_\tau(Y_i - X_i\beta_\tau) \quad (2)$$

The minimization problem of equation 2 can be reformulated and solve efficiently as a linear programming problem:

$$\hat{\beta}_\tau = min_{\beta_\tau \in R^k} \sum_{i:Y_i \geq X_i\beta_\tau} \tau\left|Y_i - X_i\beta_\tau\right| + \sum_{i:Y_i \geq X_i\beta_\tau} (1-\tau)|Y_i - X_i\beta_\tau| \quad (3)$$

For $\tau \in (0,1)$ and under some regularity conditions $\hat{\beta}_\tau$ is asymptotically normal:

$$\sqrt{N}(\hat{\beta}_\tau - \beta_\tau) \xrightarrow{d} N(0, \tau(1-\tau)\, D^{-1}\Omega_x D^{-1}) \quad (4)$$

where

$$D = E(f_y(X\beta)XX') \text{ and } \Omega_x = E(X'X), \quad (5)$$

with f_y being the probability distribution function. Inference for quantile regression parameters can be made with the regression rank-score tests or with the bootstrap methods. The latter is being utilized by the present study.

3. Data Description

The data for the empirical analysis are daily observations on the implied volatility index of gold Share options (GVZ), the net asset value of the price per share of the US Oil Fund options (USO) and the value of the Currency Share Euro Trust (FXE). Data cover more than a decade, spanning from June 3rd, 2008 to May 11th, 2021. Data observations include the global financial and economic crisis in 2008 (collapse of Lehman Brothers in September 2008), the financial crisis in the EU 2012-2015 (Greece, Italy, Portugal, Spain, Ireland) as well as the recent economic crisis due to the Covid-19 pandemic.

The Gold Volatility Index (GVZ) measures the market's expectation of thirty-day volatility of gold prices. The GVZ is derived by applying the VIX methodology to options on SPDR Gold Shares (GLD). The VIX methodology was developed by the CBOE in order to measure the market's expectation of short-run (thirty days) forward looking volatility of the underlying asset. In the case of gold, the CBOE volatility index (GVZ) is based on the performance of the GLD, where GLD is an exchange-traded fund (ETF) that represents fractional, undivided interest in the SPDR Gold Trust, which primarily holds gold bullion. The performance of GLD is intended to reflect the spot price of gold, less fund expenses. GLD first began trading on the New York Stock Exchange in November 2004. On the other hand, the Chicago Board Options Exchange started calculating and distributing the Gold VIX (GVZ) in June of 2008.

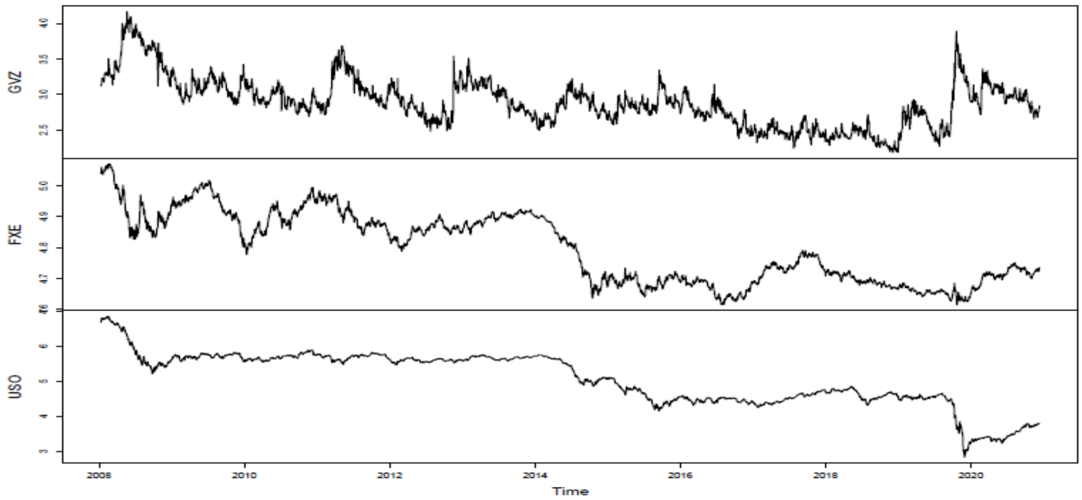
Future volatility (implied volatility) is the most significant variable in the option pricing model and is often referred as the investors' "fear gauge". In the case of gold (GVZ), market participants can improve certainty with respect to the gold price trends by looking at the implied volatility of gold (GVZ).

USO is an exchange traded fund offering investors exposure to crude oil price changes. The objective of the USO is the daily percentage changes of its net asset value to reflect the daily percentage changes of the price of the WTI, light sweet crude oil.[4] Its benchmark is the near month oil futures contract traded on the New York Merchantile Exchange (NYMEX). The United States Oil Fund was founded in April of 2006.

FXE is an exchange traded fund with holdings of physical euros on demand deposits in euro denominated bank accounts.[5] Accordingly, the daily percentage changes of the FXE intent to reflect the daily percentage changes of the $US/Euro exchange rate, less fund expenses. CBOE began trading FXE options in January of 2008.

Figure 3 presents the evolution of the natural logarithms of the GVZ, the FXE and the USO for the specified time period. It appears that FXE and USO move together for most of the time, with the exception of the time period between 2010-2012, with FXE being more volatile than USO. For the time period that corresponds to the Covid-19 pandemic, the implied volatility of gold exhibits a downward trend whereas the USO and FXE appear to move upwards. In general, the two-time series (FXE and USO) appear to generally move in opposite directions with the implied volatility of gold (GVZ).

Figure 3: Natural logarithms of GVZ, FXE and USO (3 June 2008 to 11 May 2021)



4 West Texas intermediate (WTI), also known as Texas light sweet, is a grade of crude oil used as a benchmark in oil pricing.

5 The Euro is the currency of nineteen (19) European Union countries.

Table 1 presents the descriptive statistics and tests on the distributions of the percentage changes (rates of change) for GVZ, FXE and USO. The rates of change (or returns) are defined as dlnX = lnXt - lnXt-1, where X is GVZ, FXE and USO, respectively.

The empirical results for the statistical significance of skewness, kurtosis and normality have been obtained with the use of the tests by D'Agostino (1970), Anscombe and Glynn (1983) and Shapiro and Wilk (1965), respectively. GVZ returns exhibit a positive and statistically significant kurtosis, pointing to leptokurtic distributions. The distribution of GVZ returns exhibits positive and significant skewness whereas that of USO is negative and statistically significant. The distribution of FXE returns exhibits positive skewness and it is statistically significant. For all three-time series (returns of GVZ, FXE and USO), the null of normality is strongly rejected at any reasonable level of significance.

Table 1: Descriptive Statistics for dl n (FXE) and dln (USO)

Statistics	dln (GVZ)	dln (FXE)	Dln (USO)
Min	-0.44596	-0.03123	-0.29189
Max	-0.48074	0.03605	0.15415
Mean	-0.00008	-0.00009	-0.00089
Skewness	0.80755	0.04428	-1.23551
Kurtosis	10.51509	5.66627	18.75483
Tests	**p-values**	**p-values**	**p-values**
Skewness	<0.01	<0.01	<0.01
Kurtosis	<0.01	<0.01	<0.01
Normality	<0.01	<0.01	<0.01

4. Empirical Model and Results

Empirical results are obtained with the estimation of the following relationship

$$\textit{Implied volatility change} = F(\textit{price change}), \tag{6}$$

where F is a potentially non-linear and unknown function. Changes in the implied volatility are measured by dlnGVZ. Price changes are measured by dlnFXE and dlnUSO, respectively. The three-time series (dlnGVZ, dlnFXE and dlnUSO) have been tested and the null hypothesis of non-stationarity has been rejected.

In order to empirically examine if gold serves as a safe haven asset, the index of the implied volatility and the negative returns of the independent variables of FXE and USO returns have been employed. A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another investment in periods of extreme market declines. On the other hand, in order to empirically investigate if gold acts as a hedge asset, the implied volatility index of gold and the average rate of returns of the independent variables of FXE and USO exchange traded funds have been utilized. A strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another investment on average.

Tables 2 and 3 present the empirical findings for the cases of FXE and USO, respectively. For the case of the exchange traded fund FXE (Table 2), and under average price returns, the values of the estimated parameters are negative and statistically significant up to the 0.6 quantile (with the exception of the 0.2 quantile). Furthermore, for the quantile levels 2%, 5% and 10% (crash quantiles under average returns), the estimated coefficients assume the highest values, in absolute terms. These findings indicate that gold volatility decreases significantly, in absolute terms, under average returns in the FXE, with the negative response being the highest at the crash quantiles. At the upper quantile levels (0.7 and up), the coefficients are not statistically significant, namely they are not statistically different than zero. These empirical results indicate that the implied volatility of gold does not react to changes in the average returns of the USO. Lastly, the symmetry in all quantile pairs is rejected at the 1% level of significance, indicating that gold's volatility response differs between the lower and the upper quantiles.

Table 2: Quantile Regression Results for FXE Returns

Quantiles	Coefficients (dlnP ⩾ 0) (hedge column)	Coefficients (dlnP< 0) (safe haven column)
2%	-0.43779*	3.7641
5%	-0.77062**	0.24626
10%	-0.45788*	-0.18235
20%	-0.20025	-0.13482
30%	-0.37823**	-0.63437
40%	-0.29783*	-1.16325***
50%	-0.45067**	-1.53245***
60%	-0.34680*	-1.85001***
70%	-0.32732	-2.25490***
80%	-0.41037	-2.83837***
90%	-0.28797	-3.90704***
95%	-0.27919	-4.77346***
98%	-0.22612	-6.54646***
Global equality of parameters:	**p-values**	**p-values**
	< 0.01	< 0.01
Test for parameter equality (H_0: symmetry):	**p-values**	**p-values**
2% and 98%	< 0.01	< 0.01
5% and 95%	< 0.01	< 0.01
10% and 90%	< 0.01	< 0.01
20% and 80%	< 0.01	< 0.01
30% and 70%	< 0.01	< 0.01
40% and 60%	0.68	0.05

(***, **, *): 1%, 5% and 10% levels of significance, respectively.
Results were obtained with the bootstrap method after 1000 replications.

Under negative returns in FXE, the estimated coefficients are not statistically significant at the lower quantile levels (2% to 30%). On the other hand, the estimated values of the parameters are negative and statistically significant from the 0.3 quantile level and up. More specifically, the estimated values of the parameters increase in absolute numbers, as we move at the upper quantile levels, with the highest values realized at the 0.95 and 0.98 quantiles. These findings indicate that the implied volatility of gold decreases significantly as we move at the upper quantile levels, namely as the negative changes in FXE get more extreme (extreme market declines).

Table 3: Quantile Regression Results for USO Returns

Quantiles	Coefficients (dlnP ⩾ 0) (hedge column)	Coefficients (dlnP< 0) (safe haven column)
2%	-0.38695***	-0.04829
5%	-0.28860**	0.08129
10%	-0.30881***	-0.01529
20%	-0.30433***	-0.26519***
30%	-0.36140***	-0.36701***
40%	-0.35949***	-0.37722***
50%	-0.37302***	-0.42965***
60%	-0.40273***	-0.70915***
70%	-0.46282***	-0.73437***
80%	-0.47691***	-0.89477***
90%	-0.47986***	-0.91227***
95%	-0.44790***	-1.16459***
98%	-0.48587***	-1.98318***
Global equality of parameters:	**p-values**	**p-values**
	0.209	< 0.01
Test for parameter equality (H_0: symmetry):	**p-values**	**p-values**
5% and 95%	0.29	< 0.01
10% and 90%	0.07	< 0.01
20% and 80%	< 0.01	< 0.01
30% and 70%	0.02	< 0.01
40% and 60%	0.16	< 0.01

(***, **, *): 1%, 5% and 10% levels of significance, respectively.
Results were obtained with the bootstrap method after 1000 replications.

For the case of the exchange traded fund USO (Table 3), and under average price returns in the USO, all the estimated coefficients are negative and statistically significant, at every given quantile level. Furthermore, the null hypothesis of global equality cannot be rejected, suggesting that changes of the implied volatility of gold do not differ statistically at different quantile levels.

Under negative returns in USO, the estimated coefficients are not statistically significant at the lower quantile levels (2%, 5% and 10%), namely they are not different than zero. On the other hand, the estimated values of the parameters are negative and statistically significant from the 0.2 quantile level and up. In addition, the estimated values of the parameters increase in absolute numbers, as we move at the upper quantile levels, with the highest values realized at the 0.95 and 0.98 quantiles. These findings indicate that the implied volatility of gold decreases significantly as we move at the upper quantile levels, namely as the negative changes in USO get more extreme (extreme market declines).

The null hypothesis of global equality is rejected at the 1% level of significance or less, suggesting that changes in the implied volatility of gold differ statistically at different quantile levels. Symmetry in quantile pairs is also rejected, at the 1% level of significance or less, for all pairs.

The empirical results presented in tables 2-3 need to be examined under the light of previous empirical outcomes. Accordingly, findings in relevant studies have suggested that the price of gold increases under currency depreciation (Joy, 2011; Reboredo, 2013c), as well as when oil prices go down (Reboredo, 2013a). These works suggest the possibility of using gold as a hedge against currency and oil movements, and as a safe haven asset against extreme declines in currency and oil prices. The empirical results of the present study indicate that the implied volatility of gold significantly decreases, or at least does not increase, under average as well as under extreme market declines in the exchange traded funds of FXE and USO. According to (Campbell and Hentschel, 1992), bad news brings higher current volatility as well as increases in future volatility, since volatility is highly persistent. This higher volatility raises the required return, resulting this way in a stock price decline. Investors anticipating these declines turn to assets that are less volatile and less risky, minimizing this way the danger of a potential capital loss.

Figure 4: FXE Average

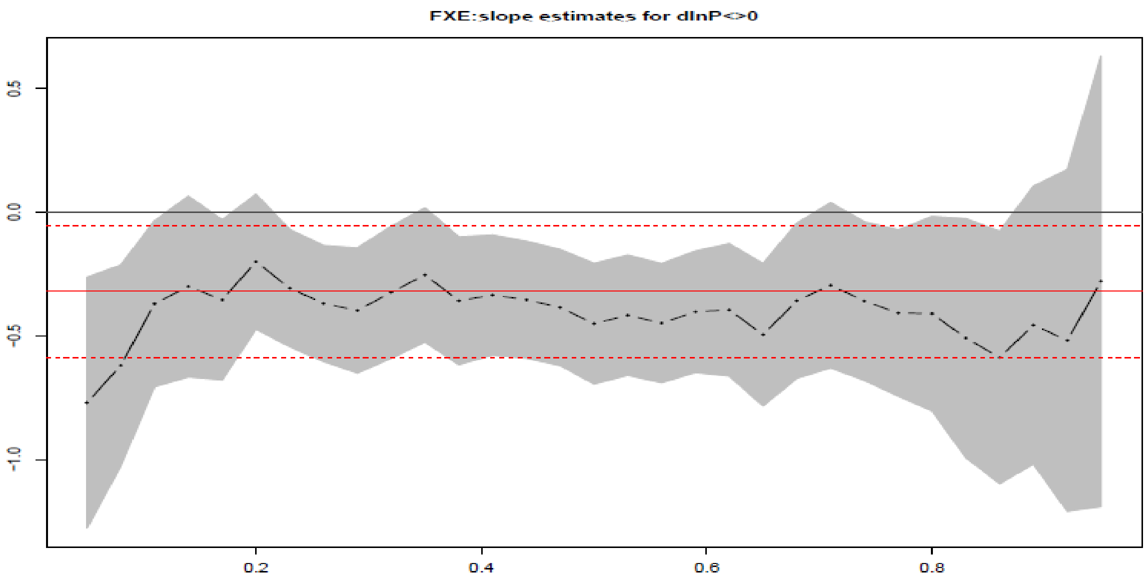
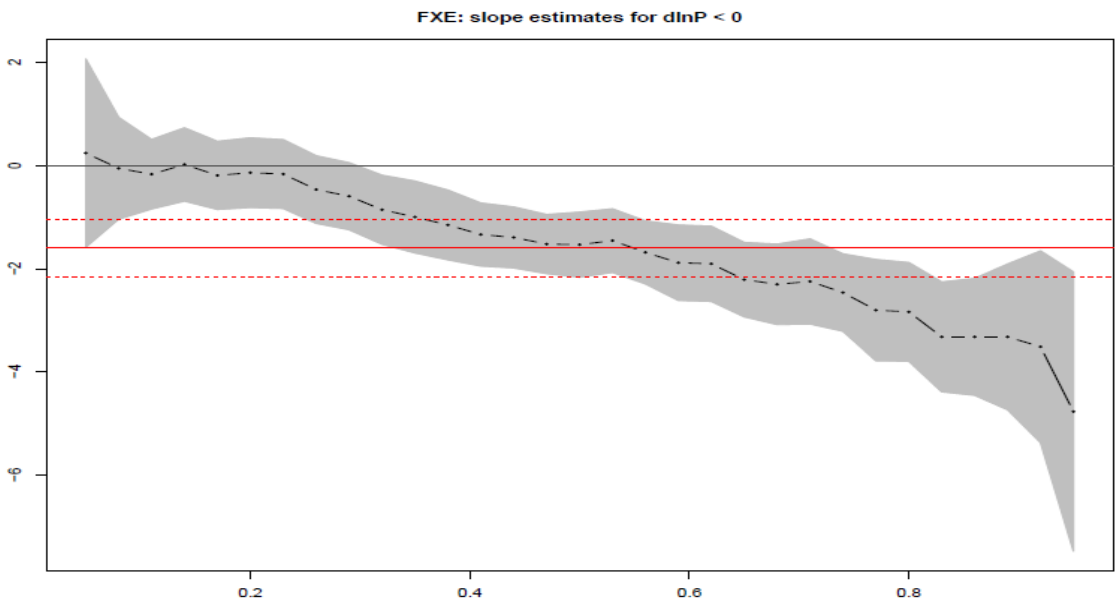
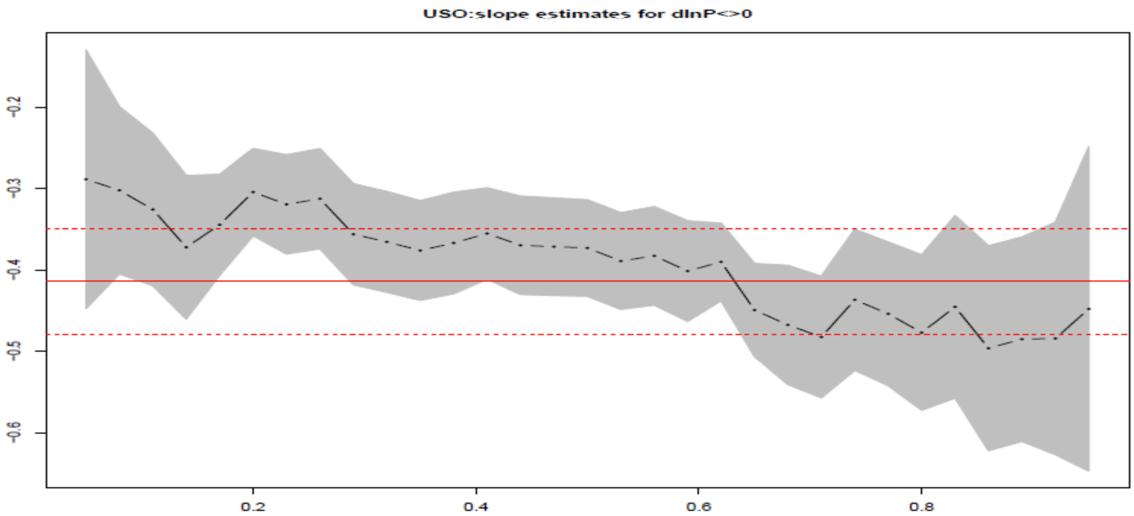


Figure 5: FXE Negative



For the case of the USO and under average returns (figure 6), the OLS coefficient is negative, statistical significant, with an estimated value of 0.42 in absolute terms. On the other hand, the estimated slopes of the quantile coefficients are lower, in absolute values, than the OLS coefficient, up to the 0.6 quantile level. Beyond that quantile level, the estimated quantile parameters obtain slightly higher values (in absolute terms) than the OLS coefficient. With a visual inspection, both the QR method as well as the OLS regression would have suggested that gold behaves as a strong hedge. Hence, the OLS parameter performs well, as compared to the QR approach, in predicting the magnitude in changes in gold's implied volatility for given changes in USO values. Under negative returns in USO (figure 7), the OLS coefficient is also negative and statistically significant. The estimated value of the OLS parameter is (approximately) 0.6 in absolute terms. On the other hand, the estimated slopes of the quantile coefficients are not statistically significant up to the 0.1 quantile level. From the 0.15 to 0.6 quantile level, the estimated values of the quantile parameters are lower, in absolute terms, than the OLS coefficient.

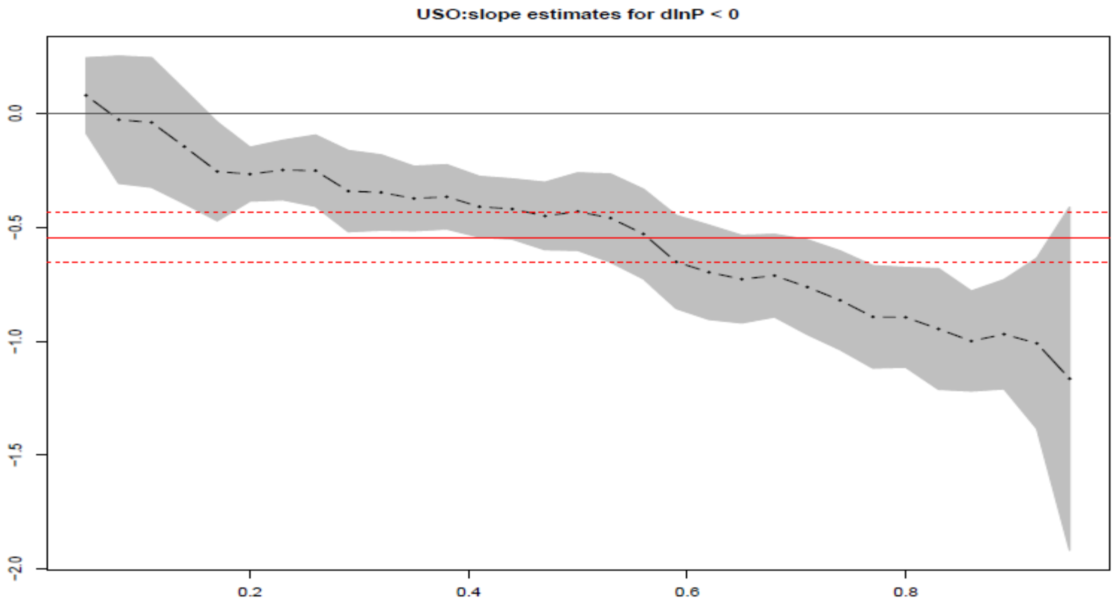
Figure 6: Average Returns in USO



As we move to the upper quantiles, the estimated values of the quantile parameters are higher (in absolute terms) than the OLS coefficient. At the 0.98 quantile, the value of the coefficient of the QR approach is 1.98 in absolute terms, whereas the 95% lower limit of the confidence interval of the OLS parameter is (approximately) 0.8. The aforementioned findings suggest that the OLS method provides a good estimate of the reaction in gold's implied volatility only for a small range of the quantile levels. In addition, as market declines in USO become more extreme (upper quantiles), the mean of changes in GVZ for given changes in USO, does not capture the true magnitude of changes in GVZ. The reason is that as the QR findings suggest, the decrease in the implied volatility of gold gets bigger and bigger as market declines in USO get more extreme.

For many years, strengthened gold prices, in combination with extreme currency movements, have attracted the attention of investors, risk managers as well as the financial media. In addition, many studies have suggested the possibility of using gold as a hedge against currency movements and as a safe-haven asset against extreme currency movements. The aforementioned fact has been proven to be quite useful for policy makers, given the association between gold and macroeconomic variables, such as interest rates and exchange rates (Reboredo, 2013b; Soytas et al., 2009). Concurrently, prior studies have indicated that gold can act as an effective safe haven against extreme oil price volatility and have proposed that portfolio risk managers could use (or use) gold to preserve or to stabilize the purchasing power of oil exporters (Reboredo, 2013b). The empirical results of the present work agree with the findings of the relevant literature so far. Accordingly, these findings suggest that gold could provide financial shelter for investors, during (extreme) market declines in oil prices as as well in the EUR/USD exchange rate, as measured by the values of their respective ETFs. The above findings are extremely useful for portfolio managers who want to maintain a diversified portfolio and who are looking for investment protection against downside risk.

Figure 7: Negative Returns in USO



5. Conclusion

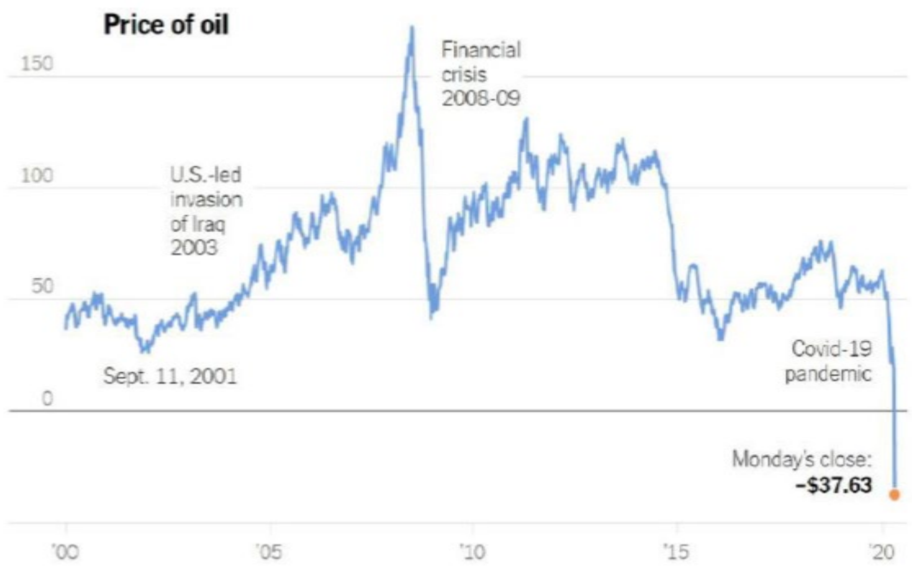
Amid the (still ongoing) coronavirus pandemic, stock markets around the globe have been experiencing high volatility and unexpected declining returns. As a prime example, on Monday, April 20th of 2020, the price of futures of WTI crude oil went negative for the first time in history. The latter means that traders had to pay buyers to take oil off their hands.6 This happened because there was no place to store all the crude the world is producing but not using due to a collapse in demand.

The objective of this work is to investigate the role of gold as a hedge or safe haven, against oil prices and exchange rates (EUR/USD) movements. In doing so, it employs the implied volatility index of gold share options (GVZ), the net asset value of the price per share of the US Oil Fund options (USO) and the value of the Currency Share Euro Trust (FXE), along with the utilization of the quantile regressions methodology. Using daily data from June 2008 to May 2021, the empirical results reveal that gold's implied volatility decreases significantly (or it is not statistically different than zero), under changes in the average returns and/or under extreme market declines in FXE and USO. The knowledge of the significant reduction in gold's implied volatility under (extreme) changes in FXE and USO returns, might be very valuable for investors and for portfolio managers. Both parties seek for investment protection against risk, particularly in reducing the risk of heavy losses in times of severe market volatility. The results indicate that gold can provide shelter in times of financial uncertainty.

Implied volatility is the market's expectation about the future realized volatility of the asset under examination and it is often referred as the investors' fear gauge. Volatility levels are largely fear driven: higher levels of fear imply higher levels of volatility. Accordingly, investors can improve certainty by focusing on the volatility. By applying technical analysis to the implied volatility of gold, the present work attempts to improve, or not, the confidence in gold against the exchange traded funds (ETFs) of the crude oil (USO) and exchange rate (EUR/USD). This information will be particularly useful to financial market participants since volatility is readily tradable, with Volatility Index (VIX) on the Chicago Board Options Exchange (CBOE) being the most prominent derivative. Exposures to volatility can be made by investing in VIX futures contract or an Exchange Traded Fund (ETF) on VIX (Hood and Malik, 2013).

The findings of this manuscript are in agreement the majority of the results in the relevant area of the finance literature. These results indicate that gold acts both as a hedge and a safe haven asset. Even though there is no theoretical model that explains why gold is usually referred to as a hedge or a safe heaven in financial markets, the reasons are many. Gold, as a financial asset, is liquid and can be traded on a futures market. Baur and McDermott (2016) also notes that gold's positive image (bright and shiny) may also contributes to this preference for gold during economic downturns. As a final note, one can suggest, that the coronavirus pandemic belongs to the "Black swan" events (Mandelbrot and Taleb, 2010). "Black swan" events are the unknown unknowns that nobody predicted or foresaw, and they have been characterized as events that carry extreme impacts. These events lie outside the realm of regular expectations and are essentially unpredictable a priori. "Black swan" events, which have never been factored in to risk models, because nobody believed, or predicted that such an event would ever take place, are precisely the type of events that force agents to re-evaluate their portfolios, generating large uncertainties and providing the grounds for safe haven purchases. Events that most closely fit the description of "Black swan" events are the 9/11 terrorist attacks in 2001 and the recent global financial and economic crisis that started in 2007. Regarding the latter, gold prices experienced an intense increase while other assets - and in particular stock prices - exhibited losses (Beckmann et al., 2015), making this way gold a strong safe haven asset. Figure 8 presents diagrammatically the price of oil from 2000 to 2020, where the "Black swan" events are pointed in the diagram.

Figure 8: WTI crude, adjusted for inflation, plotted weekly. Source: Refinitiv by the New York Times



This work appears to be the first that has considered the quantile regressions, along with the market of exchange traded funds (ETFs) and the index of gold's implied volatility, in order to make inferences about gold's hedge and/or safe haven properties One avenue for future research may involve the utilization of alternative flexible quantitative tools such as the nonparametric quantile regressions or the parametric / non-parametric copulas. Given the significant importance of the issue, further research on this elaborate topic is certainly warranted.

Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Anand, R. and Madhogaria, S. (2012). Is gold a 'safe-haven'? An econometric analysis. Procedia Economics and Finance, 1:24–33.

Anscombe, F. J. and Glynn, W. J. (1983). Distribution of the kurtosis statistic b 2 for normal samples. Biometrika, 70(1):227–234.

Baffes, J. (2007). Oil spills on other commodities. The World Bank.

Baur, D. G. and Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review, 45(2):217–229.

Baur, D. G. and McDermott, T. K. (2010). Is gold a safe haven? International evidence. Journal of Banking & Finance, 34(8):1886–1898.

Baur, D. G. and McDermott, T. K. (2016). Why is gold a safe haven? Journal of Behavioral and Experimental Finance, 10:63–71.

Beckmann, J., Berger, T., and Czudaj, R. (2015). Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. Economic Modelling, 48:16–24.

Bredin, D., Conlon, T., and Potì, V. (2017). The price of shelter-downside risk reduction with precious metals. International Review of Financial Analysis, 49:48–58.

Campbell, J. Y. and Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics, 31:281–318.

Capie, F., Mills, T. C., andWood, G. (2005). Gold as a hedge against the dollar. Journal of International Financial Markets, Institutions and Money, 15(4):343– 352.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of financial Economics, 10(4):407–432.

Ciner, C., Gurdgiev, C., and Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. International Review of Financial Analysis, 29:202–211.

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. Biometrika, pages 679–681.

Fousekis, P. (2019). Crude oil price and implied volatility: Insights from nonparametric quantile regressions. Studies in Economics and Finance. 36(2): 168-182.

Hammoudeh, S. and Yuan, Y. (2008). Metal volatility in presence of oil and interest rate shocks. Energy Economics, 30(2):606–620.

Hood, M. and Malik, F. (2013). Is gold the best hedge and a safe haven under changing stock market volatility? Review of Financial Economics, 22(2):47–52.

Joy, M. (2011). Gold and the us dollar: Hedge or haven? Finance Research Letters, 8(3):120–131.

Koenker, R. and Bassett Jr, G. (1978). Regression quantiles. Econometrica: journal of the Econometric 4 Society, pages 33–50.

Koenker, R. and Hallock, K. F. (2001). Quantile regression. Journal of Economic Perspectives, 15(4):143–156.

Mandelbrot, B. B. and Taleb, N. N. (2010). Focusing on those risks that matter. The known, the unknown, and the unknowable in financial risk management: Measurement and theory advancing practice, 47.

McCown, J. R. and Zimmerman, J. R. (2006). Is gold a zero-beta asset? Analysis of the Investment

Potential of Precious Metals (July 24, 2006).

Narayan, P. K., Narayan, S., and Zheng, X. (2010). Gold and oil futures markets: Are markets efficient? Applied energy, 87(10):3299–3303.

Reboredo, J. C. (2013a). Is gold a hedge or safe haven against oil price movements? Resources Policy, 38(2):130–137.

Reboredo, J. C. (2013b). Is gold a hedge or safe haven against oil price movements? Resources Policy, 38(2):130–137.

Reboredo, J. C. (2013c). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. Journal of Banking & Finance, 37(8):2665–2676.

Reboredo, J. C. and Rivera-Castro, M. A. (2014). Can gold hedge and preserve value when the US dollar depreciates? Economic Modelling, 39:168–173.

Sari, R., Hammoudeh, S., and Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. Energy Economics, 32(2):351–362.

Shapiro, S. S. andWilk, M. B. (1965). An analysis of variance test for normality (complete samples). Biometrika, 52(3/4):591–611.

Sjaastad, L. A. (2008). The price of gold and the exchange rates: Once again. Resources Policy, 33(2):118–124.

Soytas, U., Sari, R., Hammoudeh, S., and Hacihasanoglu, E. (2009). World oil prices, precious metal prices and macroeconomy in Turkey. Energy Policy, 37(12):5557–5566.

Zhang, Y.-J. and Wei, Y.-M. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. Resources Policy, 35(3):168–177.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

DO ECONOMIC FORECASTERS BELIEVE THE STOCK MARKET IS EFFICIENT? EVIDENCE FROM GERMANY

Richard Deaves[1]; Michael Schröder[2]; Adam Stivers[3*]; Ming Tsang[3]

1. McMaster University, Canada
2. ZEW – Leibniz Centre for European Economic Research, Germany
3. University of Wisconsin-La Crosse, Unites States of America

* Corresponding Author: Adam Stivers, College of Business Administration, Department of Finance, University of Wisconsin-La Crosse, 1725 State St., La Crosse, WI, 54601, ✉ astivers@uwlax.edu

Abstract

The perception of market efficiency is quite different from the reality of market efficiency. We show using a large survey of German market forecasters that few respondents consistently believe that the stock market is currently efficient and will remain so. Past volatility tends to erode the view that the market is efficient and strengthen the belief that the market is inefficient.

JEL codes: G14; D83; D84

Keywords: market efficiency; investor beliefs; forecasting.

1. Introduction

A long-running debate in financial economics is the extent to which financial markets embody informational efficiency. While we do not expect prices to be precisely equivalent to intrinsic values at all times according to a strict "price-is-right" version of efficiency because there have to be incentives for analysis (Grossman and Stiglitz, 1980), proponents of efficiency argue that prices are close enough to correct levels most of the time so that abnormal returns are not available to investors net of analysis and transaction costs (Fama, 1998). The evidence is famously inconclusive.[1] One problem is the data can be read in different ways: one researcher's anomaly is another researcher's risk premium (McLean and Pontiff, 2016). Relative pricing controversies can be avoided by aggregation to the level of the market, with the question then reframed to whether or not market index levels are "right." Again, problematically, abundant work pointing at aggregate return predictability can be read as inefficiency and/or time-varying risk premia (e.g., Campbell and Thompson, 2008; Welch and Goyal, 2008; Kelly and Pruitt, 2013).

The once-firmly-held academic view in favor of the efficient market hypothesis can perhaps best be summarized by the words of Michael Jensen (1978): "I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis." Despite Jensen's perhaps-optimistic statement (which predated the establishment of the iconoclastic finance sub-field of behavioral finance), the jury remains out on the extent to which markets are efficient.[2] Recently, an alternative to the efficient

[1] See Shleifer (2000) and Ackert and Deaves (2009) for numerous references.
[2] For a survey on empirical findings related to market efficiency, see Lim and Brooks (2011).

market hypothesis has gained favor in the form of the adaptive market hypothesis. According to one alternative to perfect efficiency, the adaptive market hypothesis of Lo (2019), efficiency (i.e., return predictability) is time-varying and path-dependent due to well-established investor heuristics. Evidence of time-varying predictability that is consistent with the adaptive market hypothesis has been reported by Kim, Shamsuddin, and Lim (2011) and Urquhart and McGroarty (2016). In other recent research, Bartram and Grinblatt (2018) find evidence against market efficiency, in that a naïve fundamental analysis can earn significant risk-adjusted returns; Manconi et al. (2019) find that on average share repurchases are associated with significant positive short- and long-term excess returns; and Fang et al. (2014) report that fund families are aware of the inefficiencies in some market segments and attempt to exploit inefficiencies through fund manager allocations. Other research, however, points to practices that appear to facilitate market efficiency: Purnanandam and Serhun (2018) find that short sellers on average make markets more efficient, while Chen, Kelly, and Wu (2020) report that after reduced analyst coverage, hedge funds' information acquisition and trading behavior mitigate the impairment of information efficiency caused by coverage reduction.

The reality of efficiency, whatever that may be, may or may not be the same as the perception of efficiency. Moreover, what academic researchers believe on the notion of efficiency may diverge widely from what private sector forecasters and practitioners believe. Indeed, it can be argued that the reality of efficiency requires the perception of some degree of inefficiency (Williams and Paton, 1997). The purpose of this paper is to provide some evidence on the level of market efficiency as perceived "in the real world." Thus, we investigate how often time-invariant efficiency views (versus perceived inefficiencies) are held in the real world.

Specifically, we examine beliefs on efficiency as revealed by the ZEW *Finanzmarkttest*, a monthly survey of over 200 private sector forecasters in Germany.[3] From 1991 to the present, this survey has solicited directional predictions (rise/fall/unchanged) for a series of key macroeconomic and financial market variables for the key industrialized economies as of six months in the future, one of which is the DAX, a broad German stock market index. Starting in 2003, ZEW survey respondents were also asked to provide quantitative forecasts, namely point estimates and 90% confidence intervals for the DAX six months ahead. Still later, starting in 2011, participants were asked whether they believed the DAX to be correctly priced. Since these last two questions are at the heart of this study, we repeat them (in their English translations):

1. *Six months ahead, I expect the DAX to stand at ____ points. With a probability of 90% the DAX will then range between _____ and _____ points. (Question 6b in survey. Respondents are expected to fill in three blanks.)*

2. *In view of the fundamentals of the DAX companies the DAX is currently overpriced [ ] fairly priced [ ] under-priced [ ]. (Question 6c in survey. Respondents are expected to tick one box.)*

The set of answers to these questions over time is the dataset used in this study. It allows us to observe the extent to which market practitioners believe the market to be efficient.[4] Importantly, it is possible to observe the form of any perceived inefficiency. For each

[3] This survey has been used in other research papers investigating market efficiency. For example, Deaves, Lüders, and Schröder (2010) use it to draw inferences on the extent to which market forecasters exhibit overconfidence.

[4] In quasi-related work, Shah, Ahmad, and Mahmood (2018) utilize a set of categorical questions to proxy for views on efficiency and examine how those views impact the prevalence of biases such as overconfidence.

forecaster at each point in time, we can slot survey responses according to the 3 x 3 matrix below.

		FORECAST (Question 6b)		
		Below trend (BT)	Equal to trend (ET)	Above Trend (AT)
VALUATION (Question 6c)	Overvaluation (OV)	1. Temporary OV	2. Steady OV	3. Bubble
	Fair valuation (FV)	4. Becoming UV	**5. EFFICIENCY**	6. Becoming OV
	Undervaluation (UV)	7. Reverse Bubble	8. Steady UV	9. Temporary UV

The rows correspond to question 6c and respondent views on over-, under-, or fair valuation. The columns correspond to question 6b, with the middle column containing forecasts "equal to trend." For present purposes, this means a forecast is within an interval centered on the past average return of the DAX. The first and last columns are for below-/above-trend cases. Some judgment of course is required for what constitutes a forecast close to trend, so we consider several intervals.

The nine cells in this matrix constitute various views on the nature of *current* and *future* inefficiency (if any). Cell #5 is synonymous with time-invariant efficiency: the DAX is correctly valued today, *and* the forecast is equal to trend so it will be correctly valued in the future. There are four pairs of cells that suggest variants of current and/or future perceived inefficiency:

1. *Cells #1 and #9. Temporary mis-valuation. The forecaster believes that the market is currently overvalued (#1)/undervalued (#9), but it will move towards its correct level over the next six months. This is because when the market is overvalued, the forecast is for below trend, and when undervalued the forecast is for above trend.*

2. *Cells #4 and #6. Correct valuation with sentiment about to appear. In one case (#6), positive sentiment will push the DAX into overvaluation, while in another case (#4) negative sentiment will push the DAX into undervaluation.*

3. *Cells #3 and #7. Bubbles or reverse bubbles. In one case (#3), there is the view that the market is overvalued and, because the forecast is above trend, will become even more overvalued (reminiscent of a bubble). In the second case (#7), we have undervaluation and a below-trend forecast, or what may be termed a "negative bubble."*

4. *Cells #2 and #8. Steady overvaluation or undervaluation. In Cell #2/Cell #8 the forecaster believes that the DAX is overvalued/undervalued but the extent of mis-valuation should not change much with the forecast being at trend.*

With these data, we address the following questions. First, what percentage of forecasters believe that the market is correctly valued? Second, given perceived inefficiency, what are on average the more common forms of inefficiency? Third, we consider time-variation and institution-variation in efficiency beliefs. Fourth, given this variation, are there variables that are useful in predicting whether forecasters will continue in their efficiency vs. inefficiency beliefs? The next section provides some empirical evidence, with a final section concluding.

2. Results

First, how common is a belief in efficiency? We use intervals of 0.25, 0.50 and 0.75 standard deviations above and below the historical mean of the six-month DAX return to signify the "trend," but concentrate discussion on the middle value. Table 1 shows average percentages within each of the nine cells across time and institutions. We also aggregate the cell-pairs 1&9, 4&6, 3&7, and 2&8 as suggested by the discussion in the previous section, as well as the cell triplets corresponding to fair valuation (4&5&6), overvaluation (1&2&3) and undervaluation (7&8&9).

Table 1: Percentage of Responses in Each Cell

Cells	0.75 SD	0.5 SD	0.25 SD
1	3.98%	7.06%	10.18%
2	11.58%	8.24%	4.44%
3	0.20%	0.46%	1.14%
4	4.19%	8.57%	20.52%
5	57.11%	51.01%	33.43%
6	1.41%	3.13%	8.76%
7	0.26%	0.68%	1.92%
8	18.78%	16.30%	10.45%
9	2.47%	4.54%	9.15%
1&9	6.45%	11.60%	19.33%
4&6	5.60%	11.70%	29.28%
3&7	0.46%	1.14%	3.06%
2&8	30.36%	24.54%	14.89%
5	57.11%	51.01%	33.43%
4&5&6	62.71%	62.71%	62.71%
1&2&3	15.76%	15.76%	15.76%
7&8&9	21.52%	21.52%	21.52%

This table shows the percentage of responses across our full sample that correspond to a given cell (see 3x3 matrix in Section 1). Cells are also grouped together: 1&9 correspond to temporary mis-valuation, 4&6 correspond to the market becoming misvalued, 3&7 correspond to a bubble or reverse bubble, and 2&8 correspond to steady mis-valuation. Cell 5 represents efficiency. Cells 4&5&6 correspond to a fair valuation response, cells 1&2&3 correspond to an overvaluation response, and cells 7&8&9 correspond to an undervaluation response. The percentages are computed based on an interval of 0.75, 0.5, or 0.25 standard deviations above and below trend.

Beginning with 4&5&6, which is invariant to assumptions about what constitutes "equal to trend," 62.7% of the time respondents believed that the market was currently correctly valued. While this is a solid majority of instances, the corollary is that well over a third of the time there was the view that the market was *not* currently correctly valued. Therefore, while a belief in current efficiency is modal, thinking that "the market has it wrong" is quite common.

Second, what form does a view that the market is inefficient assume? As stated above, most of the time people thought the market was correctly valued, but when they did not take this view, a belief in undervaluation was a little more common than overvaluation (21.5% vs. 15.8%). A belief in both current and future correct valuation resides in cell #5 alone, whose size is dependent on how wide our "equal to trend" interval is. Between 33.4% and 57.1% (depending on the width of the interval) of the time people believed that markets were then and would remain efficient. While the upper bound is a high percentage of responses, the fact is that it is a far from universal view. As for specific variants of inefficiency, and from this point on using a 0.5 SD interval, the only cells with very sparse responses are #3 and #7, implying that few saw either bubbles or reverse bubbles in the market. Some saw the market as correctly valued but moving away from correct valuation (11.7%), while a roughly equal number (11.6%) saw the market as temporarily misvalued but moving in the right direction. The largest non-efficient group, at 24.5%, saw the market as misvalued but without any self-correction coming in the near future.

Table 2: Percentage of Responses across Institutions and over Time

	100%	100%-90%	90%-80%	80%-70%	70%-60%	60%-50%	50%-40%	40%-30%	30%-20%	20%-10%	10%-0%
1&9	0.00%	0.00%	0.00%	1.73%	1.73%	0.43%	2.60%	3.90%	7.36%	21.65%	60.61%
4&6	0.00%	0.00%	0.43%	0.00%	0.87%	0.43%	1.73%	2.60%	8.66%	24.68%	60.61%
3&7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.43%	2.16%	97.40%
2&8	0.43%	0.87%	0.87%	1.73%	2.60%	5.19%	10.82%	10.82%	19.05%	29.00%	19.05%
5	0.87%	1.30%	6.49%	12.55%	16.88%	17.32%	16.02%	6.06%	9.96%	6.49%	6.93%

This table shows the percentage of respondents (based on their institution) that are in a given cell (or pair of cells), shown in each row, a given percentage of the time across our full sample, shown in each column. The percentages are computed based on an interval of 0.5 standard deviations above and below trend. Institutions are dropped if the total number of survey responses in the sample is less than five.

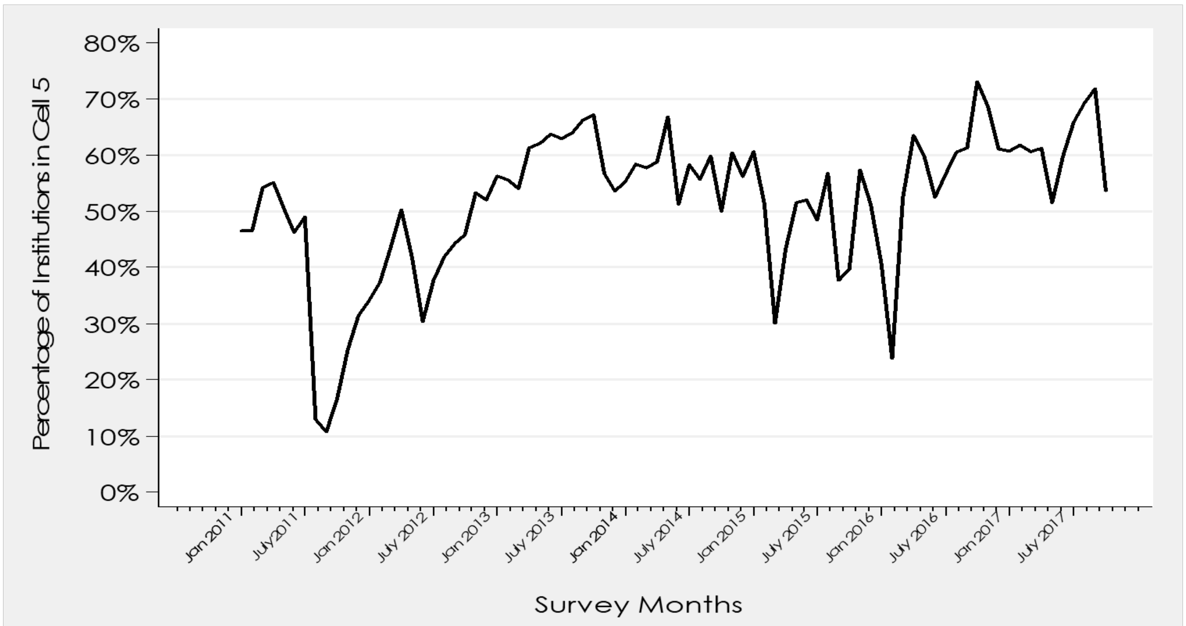
Third, considering variation in efficiency beliefs across responding institutions as well as over time and referring to Table 2, it is evident that very few institutions maintain a view that markets remain efficient over different market environments: indeed, less than 1% of institutions always locate themselves in cell #5, a far from overwhelming endorsement of efficiency.[5] Further, less than 10% (0.87 + 1.30 + 6.49) of forecasters believed that the market was efficient 80% of the time or more. Respondents frequently moved from cell to cell: only about 4%/2%/12% of answers are located in 1&9, 4&6, or 2&8, respectively, with 50% frequency or better. There is also time-variation. For example, Figure 1 shows substantial volatility in the percentage of institutions falling in cell #5 at each point in time. As few as 10% of respondents were in cell #5 in the fall of 2011, and as many as 70% were in cell #5 both in 2016 and 2017. Times when many institutions drop from cell #5 often occur when there are substantial changes in the stock market, such as a market decline or an increase in volatility. For example, in the fall of 2011, the DAX dropped substantially. These results are consistent with the adaptive market hypothesis, in that forecaster views on efficiency are time-varying.

This leads to our fourth question: what factors were associated with a belief in efficiency or inefficiency? Some exploratory monthly regressions, shown in Table 3, are suggestive. Here, we aggregate into monthly data and examine the percentage of respondents, by month, that fall within each cell. The explanatory variables are the previous month's 6-month return, the same variable squared (representing volatility), and the percentage of respondents within the same cell/cell group in the previous month (representing persistence). If one believed in efficiency (or rather, a particular form of inefficiency) in the previous month, is there is a higher likelihood of maintaining this view going forward? The answer is yes, since for all cases the lagged own cell/cell group is positive and highly statistically significant. As for past returns, if one witnesses a high [low] past return there will be an increased tendency to see the market as overvalued [undervalued], leading to an expectation of future below-trend [above-trend]

[5] The results in Exhibits 2-4 use 0.5 standard deviations to establish the trend. The results for 0.25 and 0.75 standard deviations are qualitatively similar. These results are unreported but available upon request from the authors.

returns. In the case of the first regression, high returns are consistent with a continued belief in efficiency. In the same regression, past *volatility* of returns was negatively associated with a continued belief in efficiency: the higher the square of six-month returns, the less likely it is that forecasters believed in efficiency. This is consistent with a view that high volatility is often excessive volatility, and inconsistent with market efficiency (Shiller, 1981). Consistent with this same view, the four non-efficiency cell-groups in Table 3 show positive (two of which are statistically significant at 5% or better) volatility coefficients, which can be interpreted as high volatility reinforcing one's belief in (a certain type of) inefficiency.

Figure 1: Percentage of Institutions in Cell 5 (Efficiency) across Time



This figure shows the percentage of respondents (by institution) that are in Cell 5 (efficiency) across the sample, based on an interval of 0.5 standard deviations above and below trend. The vertical axis is the percentage of institutions that are in Cell 5, and the horizontal axis lists the years and months.

Table 3: Factors that Influence the Belief in Efficiency

	% Cell 5	% Overvalued	% Undervalued	% Below Trend	% Above Trend
Constant	27.268*** (4.65)	2.268** (1.99)	5.037*** (3.57)	7.960*** (4.94)	6.512*** (5.28)
R(t-6:t-1)	0.423*** (4.56)	0.144*** (3.00)	-0.444*** (-4.18)	0.109** (2.11)	-0.584*** (-4.61)
R(t-6:t-1)²	-0.030*** (-3.64)	0.004 (0.79)	0.017** (2.55)	0.005 (1.39)	0.019*** (3.10)
Lag(y)	0.518*** (5.49)	0.785*** (12.25)	0.727*** (9.48)	0.423*** (4.01)	0.253** (2.52)
Adj. R²	0.7017	0.7247	0.8244	0.3335	0.5763

This table shows the results of monthly regressions (based on the historical DAX trend that uses +/- 0.5 standard deviations from the mean), where the dependent variable is listed in the column heading. Newey-West standard errors are used with a lag=6. The first regression uses the percentage of respondents that are within cell 5 (efficiency) as the dependent variable, the next two columns use the percentage of respondents that answer that the DAX is currently over-/under-valued as the dependent variable, and the final two columns use the percentage of respondents that give a forecast below/above the historical trend of the DAX six-month returns. R(t-6:t-1) is the lagged six-month DAX return, R(t-6:t-1)² is the square of this return (to proxy for volatility), and Lag(y) is the previous month's value of that regression's dependent variable. The adjusted R-squared value is also reported.

**** indicates significance at a 1% level, ** at a 5% level, * at a 10% level.*

3. Conclusion

In this exploratory study, we attempt to infer the market efficiency beliefs of economic forecasters. We do so by examining forecasters' survey responses to both a question on valuation of the German DAX and a six-month forecast of the DAX index. This allows us to examine if the forecasters believe the market is currently correctly valued, and if it will remain so. Our results show that, while typically about half of all forecasters believe that the market is efficient at a given point in time, less than 10% of forecasters in the sample maintain this view as often as 80% of the time.

We also show that both past DAX returns and volatility influence forecasters' inferred beliefs. For example, high past returns tend to strengthen the view that the market is and will remain efficient. Additionally, high volatility is associated with a reduced [increased] likelihood of believing markets are efficient [inefficient].

To our knowledge, this is the first attempt to categorize the market efficiency views of forecasters in this fashion. While the cells that each survey response fits into are impacted by our choice of historical trend, these explanatory results appear to be robust. It is clear that the ZEW forecasters view both the current valuation of the stock market and the future outlook for the market differently as market conditions change. Thus, our survey respondents do not view the stock market as *always* efficient. Rather, it is apparent that they view the market as mostly efficient or efficient most of the time. Our findings also line up with the time-varying efficiency proposed by the adaptive market hypothesis.

Future work could examine if individual characteristics of the respondents or their institution impact their views. For example, are males or females more likely to believe in efficiency? Do more experienced economists/forecasters tend to believe in efficiency more often than inexperienced ones? It is also possible that other economic or market variables, in addition to the ones we examine, matter. Finally, the implications of results such as these could be further explored. Do institutional investors modify their trading strategies in a manner consistent with these findings? Overall, do traders change their behavior when they are more likely to view the market as efficient? The hope is that this exploratory study inspires investigation of these and other questions.

References

Ackert, L., & Deaves, R. (2009). *Behavioral finance: Psychology, decision-making, and markets*. Cengage Learning.

Bartram, S. M., & Grinblatt, M. (2018). Agnostic fundamental analysis works. *Journal of Financial Economics*, *128*(1), 125-147.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average?. *The Review of Financial Studies*, *21*(4), 1509-1531.

Chen, Y., Kelly, B., & Wu, W. (2020). Sophisticated investors and market efficiency: Evidence from a natural experiment. *Journal of Financial Economics*, *138*(2), 316-341.

Deaves, R., Lüders, E., & Schröder, M. (2010). The dynamics of overconfidence: Evidence from stock market forecasters. *Journal of Economic Behavior & Organization*, *75*(3), 402-412.

Fama, E. F. (1998). Market efficiency, long-term returns and behavioral finance. *Journal of Financial Economics,* 49: 283-306.

Fang, J., Kempf, A., & Trapp M. (2014). Fund Manager Allocation. *Journal of Financial Economics*, 111(3): 661-674.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American economic review*, *70*(3), 393-408.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics*, 6(2/3), 95-101.

Kelly, B., & Pruitt, S. (2013). Market expectations in the cross‐section of present values. *The Journal of Finance*, *68*(5), 1721-1756.

Kim, J. H., Shamsuddin, A., & Lim, K. P. (2011). Stock return predictability and the adaptive markets hypothesis: Evidence from century-long US data. *Journal of Empirical Finance*, *18*(5), 868-879.

Lim, K. P., & Brooks, R. (2011). The evolution of stock market efficiency over time: A survey of the empirical literature. *Journal of Economic Surveys*, *25*(1), 69-108.

Lo, A. W. (2019). *Adaptive markets: Financial evolution at the speed of thought*. Princeton University Press.

Manconi, A., Peyer, U., Vermaelen, T. (2019). Are Buybacks Good for Long-Term Shareholder Value? Evidence from Buybacks around the World. *Journal of Financial and Quantitative Analysis*, 54(5), 1899-1935.

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability?. *The Journal of Finance*, *71*(1), 5-32.

Purnanandam, A., & Seyhun, H. N. (2018). Do short sellers trade on private information or false information?. *Journal of Financial & Quantitative Analysis*, *53*(3).

Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2018). Heuristic biases in investment decision-making and perceived market efficiency. *Qualitative Research in Financial Markets*.

Shiller, R. J. (1981). The Use of Volatility Measures in Assessing Market Efficiency. *Journal of Finance*, *36*(2), 291-304.

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*. OUP Oxford.

Urquhart, A., & McGroarty, F. (2016). Are stock markets really efficient? Evidence of the adaptive market hypothesis. *International Review of Financial Analysis*, *47*, 39-49.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), 1455-1508.

Williams, L. V., & Paton, D. (1997). Does information efficiency require a perception of information inefficiency?. *Applied Economics Letters*, *4*(10), 615-617.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

IS BITCOIN IMMUNE TO THE COVID-19 PANDEMIC?

S. Thomas Kim[1]; Svetlana Orlova[1]

1. Collins College of Business, The University of Tulsa

* Corresponding Author: Svetlana Orlova, Collins College of Business, Helmerich Hall 112-B, The University of Tulsa, 800 South Tucker Drive, Tulsa, OK 74104, United States,
✉ svetlana-orlova@utulsa.edu

Abstract

This study examines how Bitcoin's trading characteristics react to the COVID-19 pandemic, using detailed futures trading data from the Chicago Mercantile Exchange. The results show that volume-weighted Bitcoin futures return responds positively to the spikes of public interest. Meanwhile, the surges of pandemic information do not harm market quality. Volume, bid-ask spread, and trading frequency remain stable, indicating that the positive price reaction is not a result of a few small, uninformed trades. Bitcoin's conditional beta on the S&P 500 index drops to near zero, while the conditional beta on gold more than doubles. These results indicate that traders have been using Bitcoin to hedge the risk associated with the pandemic outbreak.

JEL codes: E42, E44, G11, G13

Keywords: Bitcoin, futures, pandemic

1. Introduction

One of the unique features that characterize cryptocurrencies is decentralization. Theoretically, decentralized cryptocurrencies can function as a hedge instrument when central authorities are in peril. However, there is mixed evidence on whether cryptocurrencies play such a role. Bouri, *et al*. (2017) argue that Bitcoin generally is not suitable for hedging but point out that Bitcoin's hedging properties depend on investment horizons. Smales (2019) argues that despite the lack of correlation between Bitcoin and other assets, the high volatility and low liquidity of the cryptocurrency disqualify it from safe-haven asset consideration. On the other hand, Corbet, *et al*. (2020) show that the volatility relationship between the main Chinese stock markets and Bitcoin evolved significantly after the COVID-19 pandemic outbreak and identify some hedging effects of the cryptocurrency.

Identifying the hedge properties of cryptocurrencies is difficult. Firstly, there has not been a significant crisis in the world economy from the point cryptocurrencies became popular until the end of 2019. Secondly, cryptocurrency markets are less established compared to traditional financial markets. Most of the cryptocurrency markets do not trade conventional financial products, and the markets are rarely regulated. The validity of the data from those markets can be questionable.[1] Lastly, the trading data is often not detailed enough.

[1] For example, Mt. Gox exchange handled 70% of Bitcoin transactions until 2014, when the exchange declared bankruptcy after a series of security breaches. Later, the CEO of the exchange was found guilty of falsifying data to inflate Mt. Gox's holdings.

We attempt to overcome these obstacles by analyzing the Bitcoin futures trading data from the Chicago Mercantile Exchange (CME) in the COVID-19 sample period. The COVID-19 pandemic created a substantial adverse effect on the world economy. If cryptocurrencies do matter in a crisis, their trading pattern should react to the event. From the market quality perspective, the CME is a well-established exchange, and the data from the CME is less likely to have inaccurate prices or mistakes in the quotes.

The CME constructed their Bitcoin futures contract to ensure arbitrage trades between the futures and the spot. When arbitrage trading is possible, the Cost-of-Carry model holds, and futures and spot prices reflect the same information.[2] Jia and Kang (2021) confirm the relationship between the futures and the spot. Kim (2021) documents that Bitcoin's convenience yield has been stable since the initiation of the futures contract. Similarly, Baig et al. (2020) show that the introduction of Bitcoin futures reduced price clustering, thus improving price discovery in the cryptocurrency market.

The CME also excels in data collection. The CME provides the Top-of-Book data that contains price, volume, and quotes with timestamps. From this data, we can construct trading activity measures that are less swayed by small, uninformed trades. Such robust variables are one of the features that differentiate our study from other works on cryptocurrencies.

We develop measures of pandemic information and examine how significant information events affect Bitcoin futures trading. We find that Bitcoin returns increase during the days of critical information. Meanwhile, we do not observe market quality deterioration signs, indicating that the pattern reflects market consensus rather than a few abnormal prices. We also find that Bitcoin's beta on the S&P 500 index significantly decreases to zero during the critical event days, while Bitcoin's beta on gold more than doubles. These results demonstrate that Bitcoin functions as a hedge against the COVID-19 crisis.

2. Data and Method

2.1 Trading Data

Most of the studies on cryptocurrencies rely on end-of-the-day or end-of-the-hour prices. However, a close look at the Top-of-Book data reveals that such prices may not represent overall trading activities. Figure 1 presents the hourly (Central Standard Time) averages of selected trading characteristics from the CME data. The prices and returns are volume weighted. The 16:00 hour has no observation because the futures market has a 1-hour break at the time.

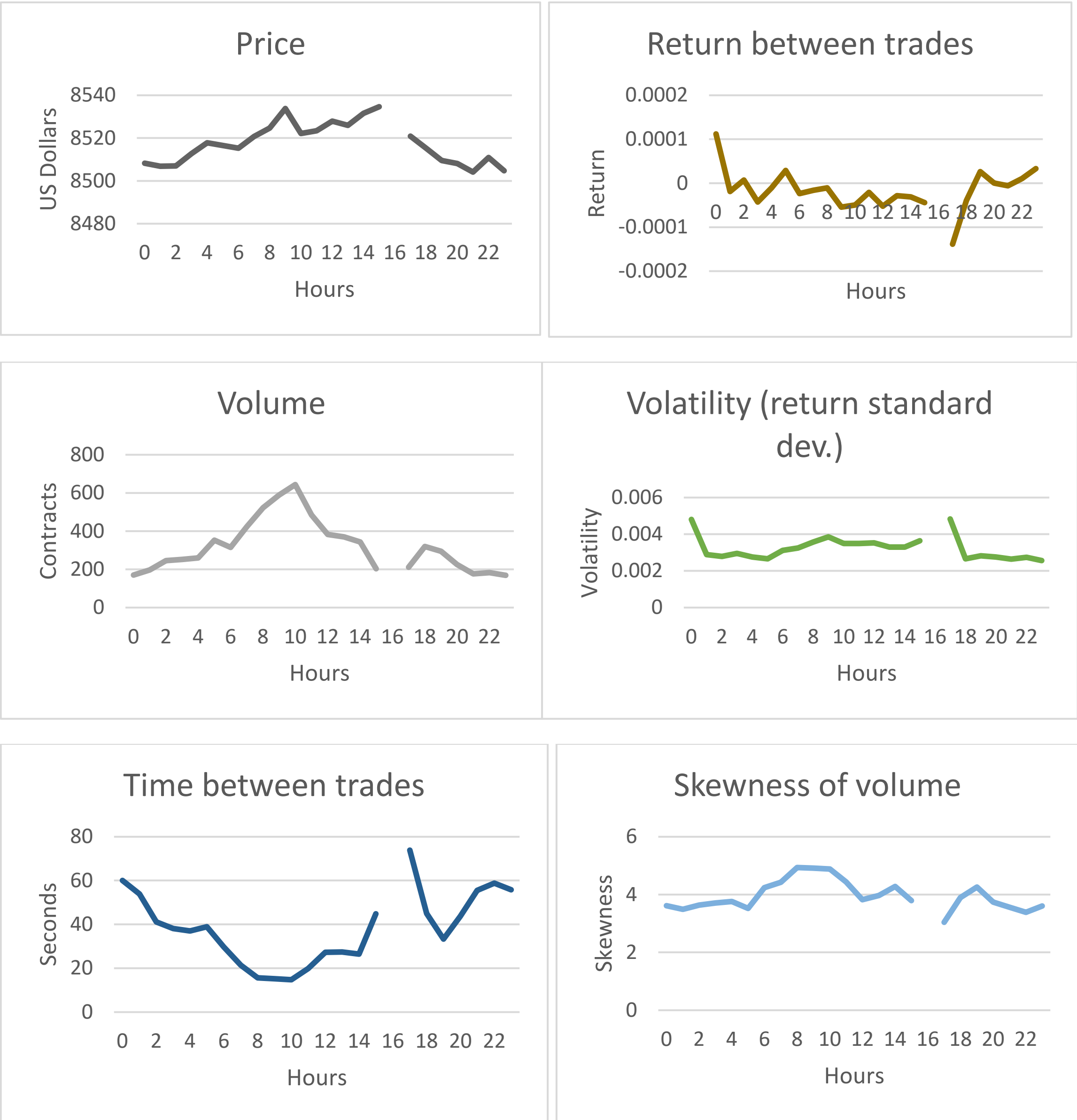
We find that return, volume, and volatility vary considerably by the hour. For example, the volatility is exceptionally high at 12:00 AM, 9:00 AM, and 5:00 PM Central Standard Time. These hours are the end of a calendar day, the maturity time of the contract, and the first hour of trading after a break. The main driver of these movements is market structure rather than information. This result demonstrates that the relationship between trading and information would be better analysed by aggregating the intra-day trading data than using end-of-time observations.

Our data period is from January 1, 2020 to June 30, 2020. The average daily trading volume is 7,332 contracts or 36,660 Bitcoins in the sample period (one CME futures contract = five Bitcoins). Note that large Bitcoin spot markets have smaller trading volumes in the same

[2] Corbet, et al. (2018) and Bauer and Dimpfl (2018) examine the relationship between Bitcoin spot and futures markets. They show that the Cost-of-Carry model holds in general between the spot and futures prices.

period. The US-Dollar-based trading volumes of spot markets are 15,931 (Coinbase), 7,695 (Kraken), and 9,588 (Bitstamp) Bitcoins per day.[3]

Figure 1: Hourly Summary of Bitcoin Futures Trading



2.2 COVID-19 Information

We match the daily summary of trading activities with two measures of the COVID-19 information.[4] First, we identify overall public interest in COVID-19 using the Google Trends search requests. We obtain data on daily search requests for "coronavirus" from Google

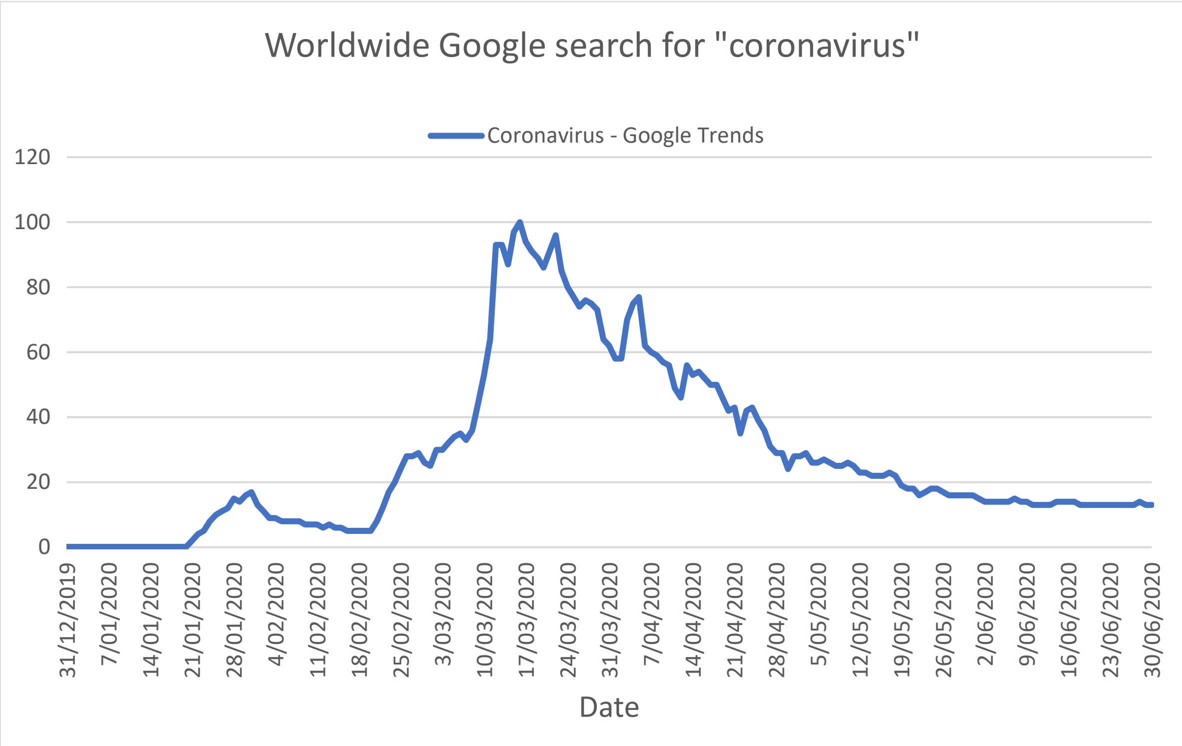
[3] For the spot market trading volumes, we used the BTC/USD daily data on the http://www.cryptodatadownload.com website.

[4] Karalevicius, et al. (2018) find that the Bitcoin prices react to the media sentiment regarding Bitcoin. Our analysis focuses on the Bitcoin futures' reaction to the information about the COVID-19 pandemic.

Trends.[5] Google Trends data is presented in a normalized format (based on time and location of a query) and ranges from 0 to 100, with 100 assigned to the data point with the highest number of searches for a specified period (and location, if applicable). Figure 2 presents the Google Trends level in our sample period. March and April 2020 exhibit higher levels of public interest.

Our second variable attempts to capture significant events or milestones in the COVID-19 pandemic. To identify the most significant events, we perform internet searches for "coronavirus/COVID-19/SARS-CoV-2/pandemic + timeline/key events/major events/ milestones," etc. within major news outlets. We include newspapers, broadcast media, news agencies, COVID-19 milestones, and response documents published by international organizations (e.g., World Health Organization (WHO)) and central banks. The following sources have published the COVID-19 timelines: WHO, CNN, Reuters, New York Times, Associated Press, and Federal Reserve Bank of St. Louis.

Figure 2: Worldwide Google search for term "coronavirus" based on Google Trends data.



We compare all the events mentioned in the above sources and designate an event as a "major event/milestone" if at least 50% of sources mention it in their timeline document.[6] The examples of the events/milestones of the COVID -19 pandemic include January 30, 2020, when the WHO declared the outbreak a Public Health Emergency of International Concern

[5] "COVID-19" can be another search keyword. However, COVID-19 is the official name of the disease introduced by the World Health Organization on February 11, 2020. We would lose more than 1 months of trends by using "COVID-19". Additionally, the number of searches that use "COVID-19" is considerably smaller compared to "coronavirus" and, in general, follows a similar trend.

[6] We try 33% or 66% as the cut-offs as well. Although the empirical results are similar with those cut-offs used, we believe 50% is the right balance. The 66% cut-off does not capture any events after March 2020. The 33% cut-off contains somewhat region-specific news.

(PHEIC). All six sources (100%) mention this event. Another example is March 13, 2020, when the former U.S. President, Donald Trump, declared a national emergency. This event appears in 83% of timeline documents. We create an indicator variable (*Coronavirus Event*) that equals to "1" on the date that significant development related to COVID-19 happened and "0" otherwise. For some events that occur on non-trading days, we assign "1" to the following trading day.[7] Table A1 in the Appendix shows that most of the announcements contain negative information, except the stimulus package announcement on March 25, 2020. Similar to the Google search pattern, the timeline events are clustered in March and April 2020.

3. Tests on the relationship between the COVID-19 and Bitcoin

3.1 Information and Reaction

We first measure Bitcoin's reactions to the COVID-19 information with multivariate regressions. In addition to the information variables, we include variables used in the prior studies (e.g., Bouri *et al.,* 2017; Philippas *et al.,* 2019; Andrada-Félix *et al.,* 2020; Corbet, *et al.,* 2020, Baur and Hoang 2020; Kim 2021) as controls. Our controls are days to maturity (*Days_to_Maturity*), convenience yield of Bitcoin futures, a daily percent change in the exchange rates between the US dollar and euro (*Euro*) as well as the US dollar and Japanese yen (*Yen*), daily stock market return (*S&P500_ret*), extreme stock market indicator, and a daily percent change in COVID-19 cases around the world (*COVIDCasesWorld_rate*).

The convenience yield variable controls the futures-spot basis. According to the Cost-of-Carry model, a futures price has a high correlation with the spot price when the convenience yield of the spot contract is stable. Kim (2021) shows that the Bitcoin spot contract has a somewhat stable convenience yield, but we control for the convenience yield in the regression to account for the irregularities during the pandemic. We calculate the convenience yield from the Cost-of-Carry model using daily CME futures price, Bitcoin Real Time Index from the CME, and 1-month T-Bill rate. The storage cost is assumed as zero. The extreme stock market indicator is similar to Baur and Hoang (2020) and captures shocks from equity markets. The variable equals one when the S&P 500 index is below or above its 10 percentile or 90 percentile value in the sample period, and zero otherwise. The model is:

$$Trading\ Characteristics_t = a + b \cdot COVID\_Info_t + c \cdot Y + \varepsilon_t \qquad (1)$$

A Trading Characteristic at day t is regressed by the COVID information variables (*Coronavirus_ Google Trends*, *Coronavirus Event*) at day t. Y is the matrix of the control variables. We convert all level variables to a (percent) change variable. A level variable is likely to be non-stationary, and a time-series model with such a dependent variable generates spurious results.[8]

As the information variables are at the daily frequency, we aggregate the Top-of-Book data. The daily return is the volume-weighted average of returns between two consecutive transactions. Small, uninformed trades will have a limited effect on volume-weighted measures. Daily volume is the sum of traded contracts per day, and volatility is the standard deviation of returns between transactions. Bid-ask spread is the difference between the volume-weighted bid and ask quotes, divided by the quote midpoint. Lastly, we acquire the

[7] Otherwise, we do not distinguish between the event date and the trading date. We find that the reactions of the futures market mostly occur on the same business day that the event happened.

[8] Also, a Tobit estimation is necessary for a level variable because the dependent variable's sign is always above zero.

time between trades by taking the volume-weighted average of time between two consecutive transactions. We estimate our model using the OLS regressions with Newey –West standard errors.

Table 1: Impact of public interest and COVID-19 milestones on Bitcoin futures trading

	Return (1)	Return (2)	Return (3)	Δ Volatility (4)	Δ Volume (5)	Δ Bid-ask spread (6)	Δ Time btw. trades (7)
Coronavirus_ GoogleTrends	**0.98[a]**	**0.97[a]**		-6.48	-0.02	8.44	0.16
(public interest)	**(3.86)**	**(3.78)**		(-1.26)	(-0.95)	(0.39)	(1.37)
Coronavirus_Event	-11.67		-8.86	527.74	0.37	1,410.39	**-15.62[b]**
(main event)	(-0.66)		(-0.47)	(1.06)	(0.27)	(1.00)	**(-1.99)**
Days_to_Maturity	0.41	0.45	0.016	-14.88	0.04	24.51	0.065
	(0.68)	(0.76)	(0.03)	(-0.99)	(1.11)	(0.76)	(0.18)
Convenience Yield	-8.04	-8.29	0.43	**375.47[c]**	0.81	782.08	0.02
	(-0.78)	(-0.80)	(0.04)	**(1.73)**	(1.27)	(1.14)	(0.00)
Euro	1,349.76	1,330.97	791.35	350.88	-161.13	87,236	1,013.80
	(1.30)	(1.29)	(0.74)	(0.01)	(-1.55)	(1.12)	(1.35)
Yen	1,557.03	1,472.10	1,830.99	-6,325.10	-67.88	-15,672	201.51
	(1.34)	(1.28)	(1.43)	(-0.27)	(-0.74)	(-0.16)	(0.32)
S&P500_ret	144.60	137.96	52.19	-3,694.24	-25.61	**-66,552[a]**	126.30
	(0.72)	(0.68)	(0.23)	(-0.64)	(-1.64)	**(-2.91)**	(1.53)
S&P500 Extreme	**-36.97[b]**	**-37.38[b]**	-5.50	1.55	0.82	153.61	-4.96
	(-2.23)	**(-2.20)**	(-0.41)	(0.00)	(0.87)	(0.12)	(-0.68)
COVIDCases	10.42	9.98	5.27	188.89	-0.46	8.44	**12.09[b]**
World_rate	(1.46)	(1.49)	(0.73)	(1.64)	(-0.73)	(0.39)	**(2.42)**
Constant	**-50.83[a]**	**-52.49[a]**	**-24.82[b]**	333.94	-0.30	-821.85	-3.99
	(-3.80)	**(-4.14)**	**(-2.00)**	(1.24)	(-0.37)	(-1.06)	(-0.70)
Observations	121	121	121	121	121	121	121
Adj. R-squared	6.85%	7.23%	-3.27%	-1.95%	-0.93%	14.61%	0.28%

This table presents the results of the OLS estimation of equation (1). The names of the dependent variables are in the first row. The Coronavirus_GoogleTrends (public interest) and Coronavirus_Event (main event) variables are the main explanatory variables. Further details on the variables are in section 3.1. The Greek letter delta (Δ) indicates that we use the difference between two consecutive observations. The coefficients on return, volatility, and spread are multiplied by 106 for visual convenience. T-values are in the parentheses, and the Newey –West standard errors are heteroscedasticity consistent.

Significance levels are indicated as follows: c = 10%, b = 5%, a = 1%.

Columns 1 and 2 in Table 1 show Bitcoin return is positively and significantly correlated with the public interest variable (*Coronavirus _Google Trends*). This pattern indicates that Bitcoin price increases when the public is more aware of (and/or more worried about) the crisis. Such a price reaction is consistent with the results of Corbet, *et al.* (2020). They measure the COVID-19 sentiment from Tweeter and find significant positive correlations between the measures and cryptocurrency returns. Compared to their study, we use volume-weighted returns and a more extended sample period (Jan 2020 - Mar 2020 vs. Jan 2020 - Jun 2020). Our result shows that Bitcoin price increase is a robust phenomenon in the pandemic period.

In addition, we do not observe any significant effect of the public interest variable on other trading characteristics. Volume, bid-ask spread, or time between transactions do not deteriorate significantly during the critical days. Such results demonstrate that the pandemic event has little impact on the market quality of Bitcoin futures. In unreported tests, we set various market quality variables as the dependent variable and check the relationship with the pandemic information. Other market quality variables, including volume volatility or skewness of volume, are not significantly associated with the pandemic information.

In column 6, the S&P 500 return has a particularly strong explanatory power for the bid-ask spread. The S&P 500 return coefficient is significant at the 1% level, and the adjusted R-squared is 15%. These numbers indicate a link between the stock market performance and the transaction cost of Bitcoin futures.

3.2 Bitcoin Betas

To further examine Bitcoin's usefulness as a hedge against the COVID-19 crisis, we analyze Bitcoin's betas. We construct the following model to determine if Bitcoin's betas change in critical times.

$$R_t = a_1 + b_1 \cdot R_{Bit,t} + b_2 \cdot R_{Bit,t} \times Pandemic_t + a_2 \cdot Pandemic_t + \varepsilon_t \tag{2}$$

R_t is the daily return of an asset, $R_{Bit,t}$ is the daily return of Bitcoin futures, and $Pandemic_t$ is an indicator variable of the pandemic information. The $Pandemic_t$ variable equals one in the days with a notable change in the pandemic information. When the $Pandemic_t$ variable is zero, equation (2) becomes a simple beta estimation model, where the coefficient b_1 is the beta. When the $Pandemic_t$ variable is one, the beta b_1 changes by the coefficient b_2. Thus, the b_2 term captures a change in beta during critical times, and the $b_1 + b_2$ term is the beta conditional on the surge of the pandemic information.

For the $Pandemic_t$ variable, we convert our *Coronavirus_ GoogleTrends* variable to an indicator that is equal to one whenever the variable is over 75 and zero otherwise. The number over 75 means the number of searches in a day is higher than the 75 percentiles of the sample period.[9]

We regress the Bitcoin return on the S&P 500 index, gold, and the Dollar index (DXY) returns. The S&P 500 index and gold returns are from Yahoo Finance and the DXY data is from Bloomberg. To reduce the noise in the end-of-the day prices, we calculate the daily return of Bitcoin futures from the daily volume-weighted average prices.[10] The estimation method is the OLS with Newey –West standard errors. Table 2 presents the results.

Regressions on the S&P 500 returns show that Bitcoin's beta is 0.19 during relatively stable times. However, the interaction variable has a negative coefficient, as the beta drops to near zero in turbulent times.[11] Bitcoin has a positive correlation with the stock market in general, but a massive negative shock breaks the link.

---

[9] We test with different thresholds such as 50 or 90 and acquire similar results.

[10] We acquire similar results by cumulating the return between Bitcoin transactions. Still, the estimated betas will be easier to interpret if both the dependent variable and explanatory variable are from the differences in daily prices.

[11] Estimation using a subsample of critical information days indicates that Bitcoin's beta is statistically indistinguishable from zero.

Table 2: Conditional betas of Bitcoin futures

	S&P 500	S&P 500	Gold	Gold	USD Index	USD Index
Bitcoin Return: b_1	**0.191**[b] **(2.59)**		**0.063**[b] **(2.48)**		-0.008 (-0.52)	
Bitcoin Return x Pandemic: b_2	-0.119 (-0.42)	0.072 (0.27)	0.078 (1.13)	**0.141**[b] **(2.18)**	-0.007 (-0.23)	-0.015 (-0.63)
$b_1 + b_2$	*0.072*		*0.141*		*-0.015*	
Constant: a_1	0.000 (0.06)	0.001 (0.49)	0.001 (1.01)	0.001 (1.39)	-0.000 (-0.48)	-0.000 (-0.59)
Pandemic: a_2	-0.010 (-0.49)	-0.010 (-0.53)	-0.002 (-0.18)	-0.002 (-0.22)	0.003 (1.08)	0.003 (1.09)
$a_1 + a_2$	*0.010*	*-0.009*	*-0.001*	*-0.001*	*0.003*	*0.003*
Adjusted R^2	4.1%	0.0%	10.2%	8.9%	2.2%	2.8%

The conditional beta of Bitcoin is estimated using equation (2).

$$R_t = a_1 + b_1 \cdot R_{Bit,t} + b_2 \cdot R_{Bit,t} \times \text{Pandemic}_t + a_2 \cdot \text{Pandemic}_t + \varepsilon_t \qquad (2)$$

R_t is the daily return of an asset, $R_{Bit,t}$ is the daily return of Bitcoin futures, and $Pandemic_t$ is the indicator variable of the COVID-19's impact. We create the indicator variable by setting its value as 1 when the number of Google searches is over 75 percentiles. The daily return is the return from the daily volume-weighted average price. We regress the Bitcoin return on the returns of the Standard & Poors 500 index and gold. The estimation method is OLS, and the Newey –West standard errors are heteroscedasticity consistent. The $a_1 + a_2$ row and the $b_1 + b_2$ row report the sum of the coefficients for visual convenience. T-values are in the parentheses.

Significance levels are indicated as follows: c = 10%, b = 5%, c = 1%.

Bitcoin's beta with the gold price is positive and significant, demonstrating that Bitcoin's price moves similar to gold. When the pandemic situation escalates, the gold beta more than doubles from 0.06 to 0.14. In a crisis, Bitcoin begins to resemble gold, the traditional hedging instrument.

We do not find a significant relationship between the Dollar index and Bitcoin returns. This result may stem from several possibilities. First, Bitcoin price is based on the US Dollar, so Bitcoin return could already include the value change in the Dollar. Second, the USD index was stable during the data period. The standard deviation of daily return is 0.52%. The index may have a low volatility because most fiat currencies were simultaneously affected by the pandemic.

4. Conclusion

This paper examines the reactions of Bitcoin's trading characteristics to the COVID-19 pandemic. Using detailed trading data from an established futures exchange, we find that volume-weighted Bitcoin futures return responds positively to the spikes of public interest. Meanwhile, the surges of pandemic information do not harm market quality. Volume, bid-ask spread, and trading frequency remain stable, indicating that the positive price reaction is not a result of a few small, uninformed trades.

Our analysis of Bitcoin's beta verifies the existence of hedge-seeking trades. Bitcoin has a positive and significant beta with the S&P 500 index in general, but the beta drops to zero during turbulent times. Similarly, we find that Bitcoin's beta on gold more than doubles in critical times.

Overall, this study demonstrates that Bitcoin has been functioning as a hedge after the pandemic outbreak. Media has been calling cryptocurrencies as "Digital Gold," mainly to describe speculative demand. After the COVID-19 crisis, perhaps the same nickname can have a different meaning, indicating that cryptocurrencies can have hedging properties similar to gold.

References

Andrada-Félix, J., Fernandez-Perez, A., Sosvilla-Rivero, S., 2020. Distant or close cousins: Connectedness between cryptocurrencies and traditional currencies volatilities. Journal of International Financial Markets, Institutions and Money 67, 101219.

Associated Press, 2020. Timeline of key events in the spread of the new coronavirus Associated Press, available at: https://apnews.com/article/f143c90d86e5887fbb74cdc40b6796da (accessed 10 September 2020)

Baig, A. S., Haroon, O., Sabah, N., 2020. Price Clustering After the Introduction of Bitcoin Futures. Applied Finance Letters, 9, 36 - 42.

Bauer, D., Dimpfl, T., 2019. Price discovery in bitcoin spot or futures? Journal of Futures Markets 39, 803-817

Baur, D., Hoang, L., 2021. A crypto safe haven against Bitcoin. Finance Research Letters, 101431.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters 20, 192-198.

CNN Editorial Research (2020), "Coronavirus Outbreak Timeline Fast Facts", CNN, September 7, available at: https://www.cnn.com/2020/02/06/health/wuhan-coronavirus-timeline-fast-facts/index.html (accessed September 10, 2020)

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., Oxley, L., 2020. Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. Economics Letters 194, 109377.

Corbet, S., Larkin, C., Lucey, B., 2020. The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. Finance Research Letters 35, 101554.

Corbet, S., Lucey, B., Maurice, P. and Samuel, V. (2018), "Bitcoin Futures—What use are they?", Economics Letters, Vol. 172, pp. 23-27.

Federal Reserve Bank of St. Louis. (2020), "Timeline of Events Related to the COVID-19 Pandemic", Federal Reserve Bank of St. Louis, available at: https://fraser.stlouisfed.org/timeline/covid-19-pandemic (accessed September 10, 2020)

Jia, J., & Kang, S. B. (2021). Do the basis and other predictors of futures return also predict spot return with the same signs and magnitudes? Evidence from the LME. Journal of Commodity Markets, 100187.

Karalevicius, V., Degrande, N., De Weerdt, J., 2018. Using sentiment analysis to predict interday Bitcoin price movements. Journal of Risk Finance 19, 56-75.

Kim, S. T., 2021. Is it worth to hold Bitcoin?, Finance Research Letters, 102090.

Philippas, D., Rjiba, H, Guesmi, K., Goutte, S., 2019. Media attention and Bitcoin prices. Finance Research Letters, 37-43.

Reuters staff, Editing by de Kretser, L., Wu, T., 2020. Timeline: How the global coronavirus pandemic unfolded, Reuters, June 28, available at: https://www.reuters.com/article/us-health-coronavirus-timeline/timeline-how-the-global-coronavirus-pandemic-unfolded-idUSKBN23Z0UW (accessed September 10, 2020)

Smales, L.A., 2019. Bitcoin as a safe haven: is it even worth considering? Finance Research Letters 30, 385–393

Taylor, D.B., 2020. A Timeline of the Coronavirus Pandemic. New York Times, August 6, available at: https://www.nytimes.com/article/coronavirus-timeline.html (accessed September 10, 2020)

World Health Organization (WHO), 2020. Timeline of WHO's response to COVID-19. World Health Organization, available at: https://www.who.int/news-room/detail/29-06-2020-covidtimeline (accessed 30 June, 2020)

COVID-19 PANDEMIC AND HERDING BEHAVIOUR IN CRYPTOCURRENCY MARKET

Samuel Asante Gyamerah[1*]

1. Kwame Nkrumah University of Science and Technology

* Corresponding Author: Samuel Asante Gyamerah, Department of Statistics and Actuarial Science, Kwame Nkrumah University of Science and Technology, Kumasi-Ghana; KNUST-laboratory for Interdisciplinary Statistical Analysis, Kumasi-Ghana, ✉ saasgyam@gmail.com

Abstract

In this paper, we examine the presence of herding in the cryptocurrency market for four distinct sub-periods (Pre and During COVID-19 period, bear and bull markets) using daily closing prices of the five largest cryptocurrencies by market capitalisation (Bitcoin, Ethereum, XRP, Stellar, and Tether) from 20 April 2019, to 31 January 2021. The study employs cross-sectional absolute deviations (CSAD) model to test for the presence of herd behaviour in the cryptocurrency market. The study results provide evidence of herd behaviour in the whole market for the selected period under study. The study also proves the presence of herding during the COVID-19 period and in the bullish market (positive market returns). These indicate that investors in the cryptocurrency market make similar trading decisions for positive market returns and during the COVID-19 pandemic period.

The study is significant to investors, regulators, and players in the cryptocurrency market to make appropriate decisions during times of uncertainty and market fears.

Keywords: COVID-19, herding behaviour, bear and bull market, cryptocurrency, cross-sectional absolute deviation

1. Introduction

As the novel coronavirus disease (COVID-19) pandemic rages across the world, the financial markets have tumbled worldwide (Khatatbeh et al., 2020; Iqbal et al., 2018). The cryptocurrency market is no exception, as the market has experienced its largest-ever Bitcoin inflow and a significant increase in price during the COVID-19 pandemic (Poyser, 2018). Moreover, when most conventional financial assets appeared to lose value freely during the COVID-19 pandemic, a considerable number of investors are closely observing the trend of cryptocurrencies. Exploring safe assets as a hedging and diversification instrument during this uncertain and adverse market crisis is a common wish of every investor. One such safe haven for investors may include cryptocurrencies (Xie et al., 2021; Mnif et al., 2020; Urquhart and Zhang, 2018).

Contrary to past financial crises where investors place their assets in safe havens such as gold, the current COVID-19 pandemic is depicted by a surge in the trading volumes of cryptocurrencies (Mnif, E. and Jarboui, A., 2021). This upward surge may be due to investors' belief in the cryptocurrency market as a safe haven or investors following the market's performance without adequate information and appreciation of the risk-reward trade-offs. Even though different macro factors such as the COVID-19 pandemic, political turmoil, economic uncertainty, and market volatility can influence the price of cryptocurrencies, their technical features based on blockchain technology give them comparative strength against these uncertainties (Colon et al., 2021). Cryptocurrency is a financial asset that can be used to buy goods and services but uses an online ledger with strong cryptography to secure online transactions without going through a financial institution. Hence, understanding investors' behaviour on the cryptocurrency market before and during the COVID-19 pandemic is critical to researchers and practitioners. The traditional finance framework takes no account of investors' rationality, leading to booms and busts in the financial market. This paper investigates the concept of behavioural finance on an investor herding in the cryptocurrency market during the pandemic. Research on herd behaviour of cryptocurrencies in the period of the COVID-19 pandemic is of interest to investors since most investors may mimic the behaviour of other investors without adequate information and appreciation of the risk-reward trade-offs. There are limited literature studies exploring the herding behaviour in the cryptocurrency market during the COVID-19 pandemic (Yarovaya, Matkovskyy, and Jalan, 2021; Rubbaniy, 2020). Yarovaya et al. (2021) analysed herd behaviour in the crypto market from 1 January 2019 to 13 March 2020 using hourly prices of the four most traded cryptocurrency markets - USD, EUR, JPY, and KRW. They indicated the presence of herding behaviour for all markets except KRW.

Nevertheless, the authors stated that COVID-19 does not heighten herd behaviour in cryptocurrency (crypto) markets for the period under study. However, the authors were quick to indicate that their results should be explained with care since the data used was based on the early stage of the pandemic. Rubbaniy (2020) investigated herd effects in more than 100 different cryptos using daily data from 1 January 2015 to 25 June 2020. The study revealed significant evidence of herd behaviour in the crypto market. There are significant discrepancies in the results from the literature mentioned above on herd behaviour of cryptos in the period of the COVID-19 pandemic. Specifically, there are limited literature studies on herd behaviour in the crypto market during this financial contagion caused by the COVID-19 pandemic. This paper makes contributions to the literature in four aspects: to investigate the existence of herd behaviour in the crypto market; to explore the presence of herd behaviour before and during COVID-19 pandemic periods; to analyse the presence of herding in bear and bull crypto market, and to provide a reference for assessing herding behaviour in the crypto markets after the pandemic subsides.

The rest of the paper is organised as follows. In section 2, the data and methodology used for the study are presented. The empirical results are presented in Section 3 and the conclusion in Section 4.

2. Data and Methodology

2.1 Data

Data used for this research consist of daily closing prices of the five largest cryptos by market capitalisation (Bitcoin, Ethereum, XRP, Stellar, and Tether) from 20 April 2019 to 31 January 2021, corresponds to a total of 652 trading days. The data are downloaded from www.coindesk.com.

Logarithmic returns (Equation 1) are used to estimate the returns for the five selected cryptos for the period under consideration.

$$r_{i,t} = \text{In}\left(\frac{p_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

where $r_{i,t}$ is the logarithmic return and $p_{i,t}$ is the closing price of Crypto i at time t and $P_{i,t-1}$ is the closing price of Crypto i at time $t-1$.

The dataset is divided into two, Pre COVID-19 (20 April 2019 - 10 March 2020) and During COVID-19 (11 March 2020 - 31 January 2021) periods. 11 March 2020 is used as the starting period because it is the day the World Health Organization (WHO) declared COVID-19 a global pandemic. Two types of markets are also considered from the dataset, bull and bear markets: positive market returns and adverse market returns, respectively.

2.2 Methodology

2.2.1 The Cryptocurrency Market

Assume a crypto market where i different cryptos, labelled from 1 to N are traded. The current trading time is $0,$ and the time period under analysis is T days. Let $r_{i,t}$ be the return of crypto i at time t, $0 \leq \mathrm{t} \leq \mathrm{T}.$ Hence, we can assume that $r_{i,t} \geq 0$ for all i, where the first and second-order moments are finite. The market index consists of a linear combination of N underlying cryptos. Let the market (m) return of the index at time t be represented by $r_{m,t}$, $0 \leq \mathrm{t} \leq \mathrm{T}$, and hence

$$r_{m,t} = \eta_{1,t}r_{1,t} + \eta_{2,t}r_{2,t} + \cdots + \eta_{i,t}r_{i,t} = \sum_{i=1}^{N} \eta_{i,t}r_{i,t} \tag{2}$$

where $\eta_{1,t}$ is the weight of crypto i at time t calculated from the market capitalisation and $r_{i,t}$ is the return of cryptocurrency i at time t. Using the market capitalisation (cap) for the selected cryptos, we can calculate the market portfolio, which is the cap-weighted market return, $r_{m,t}$ given in Equation 2.

The calculated index $r_{m,t}$ using Equation 2 serves as a benchmark for the five selected cryptos used in this study.

2.2.2 Herding Detection

Chang et al. (2000) explained a linear association between an asset's return dispersion and the absolute value of market returns of asset pricing models; hence they constructed the cross-sectional absolute deviation (CSAD) model. The linear model predicts that during extreme market movement, the returns of any asset will drift from the market returns. Contrary, during times of stable periods, individual returns spread closer to market returns. CSAD is a typical measure used to capture the dispersion of an asset's returns from market returns. In this paper, the CSAD model is used to analyse and interpret the concept of herd behaviour in the crypto market. The CSAD is given as,

$$CSAD_t = \frac{\sum_{i=1}^{N}\left|r_{i,t} - r_{m,t}\right|}{N} \tag{3}$$

Where $CSAD_t$ is the cross-sectional absolute deviation for i_{th} crypto at time t, N is the number of crypto's, $r_{m,t}$ is the market return estimated on a day-to-day basis at t, and $r_{i,t}$ has its usual meaning. In this paper, CSAD assesses the presence of herd behaviour using the ordinary least square (OLS) regression technique. Consequently, the OLS regression is formulated as in Equation (4),

$$CSAD_t = \kappa_0 + \kappa_1\left|r_{m,t}\right| + \kappa_2\,(r_{mt}^2) + \epsilon_t \tag{4}$$

where, κ_0, κ_1, and κ_2 are the regression coefficients, $\left|r_{m,t}\right|$ is the absolute value of market return at time t, ϵ_t is the error term and $r_{m,t}$ has the usual meaning as above. Equation (4) is used in exploring the existence of herd behaviour in the crypto market. To prove the existence of herding, κ_2 must be negative and significant. More particularly, Equation (5) is used to evaluate the effect of COVID-19 on herding,

$$CSAD_t = \kappa_0 + \kappa_1 D^{COVID}\left|r_{m,t}\right| + \kappa_2\left(1 - D^{COVID}\right)\left|r_{m,t}\right| + \kappa_3 D^{COVID}\left(r_{m,t}\right)^2 + \kappa_4\left(1 - D^{COVID}\right)\left(r_{m,t}\right)^2 + \epsilon_t \quad (5)$$

Here, D^{COVID} is a dummy variable and equal to 1 after 11 March 2020 (when COVID-19 was declared as a pandemic) and zero otherwise. Negative and significant values of κ_3 and κ_4 proves the presence of herd behaviour following (before) the COVID-19.

To investigate the presence of herding in the bear and bull market, the following regression equations (Equation 6 and 7) are used,

$$CSAD_t^{bull} = \kappa_0 + \kappa_1^{bull}\left|r_{m,t}^{bull}\right| + \kappa_2^{bull} r_{mt}^{2\,bull} + \epsilon_t \quad (6)$$

$$CSAD_t^{bear} = \kappa_0 + \kappa_1^{bear}\left|r_{m,t}^{bear}\right| + \kappa_2^{bear} r_{mt}^{2\,bear} + \epsilon_t \quad (7)$$

where $r_{m,t} > 0$ and $r_{m,t} < 0$ for bull and bear market respectively.

3. Empirical Analysis

3.1 Descriptive Statistics

Daily returns were computed using Equation (1) for the selected period. The price and returns dynamics of the five cryptos used in this study are presented in Figures 1 and 2, respectively. Clearly, from Figure 1, the market for these cryptos experienced volatile behaviour starting after the first three months of 2020 except for Tether for which had a sharp price increase around March 2020 and remained somehow stable. These price dynamics can create the right conditions for the emergence of herding behaviour on the crypto market.

Figure 1: Price dynamics of Bitcoin, Ethereum, XRP, Stellar and Tether from 20 April 2019 to 31 January 2021

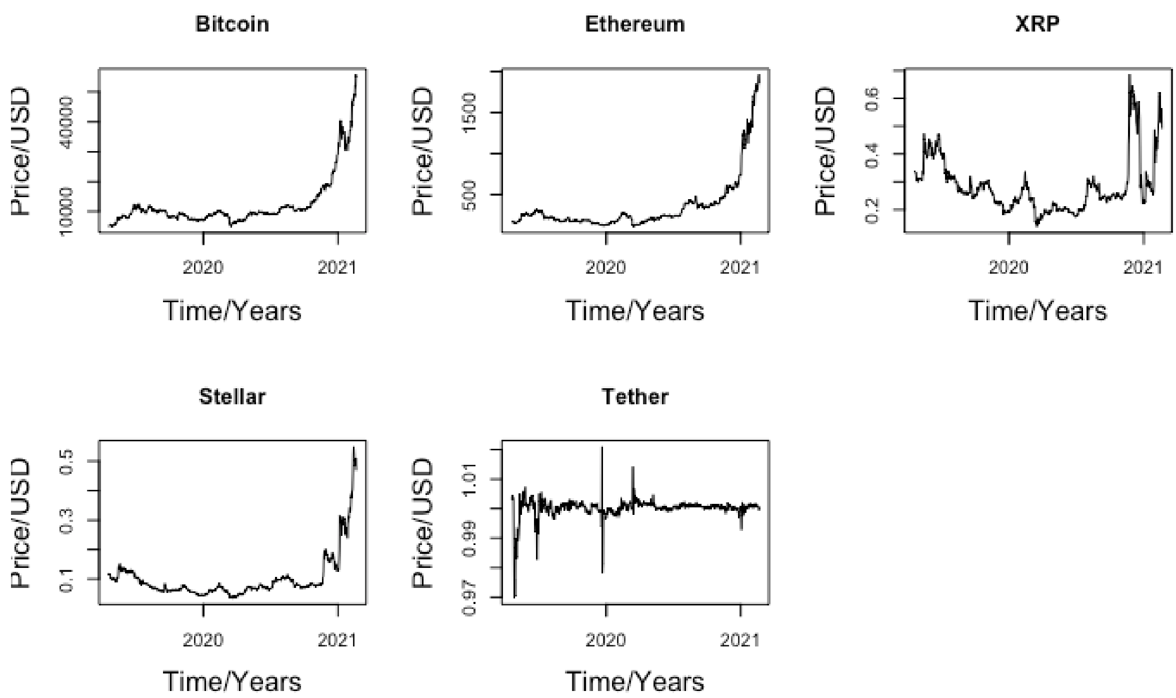


Figure 2: Returns dynamics of Bitcoin, Ethereum, XRP, Stellar and Tether from 20 April 2019 to 31 January 2021

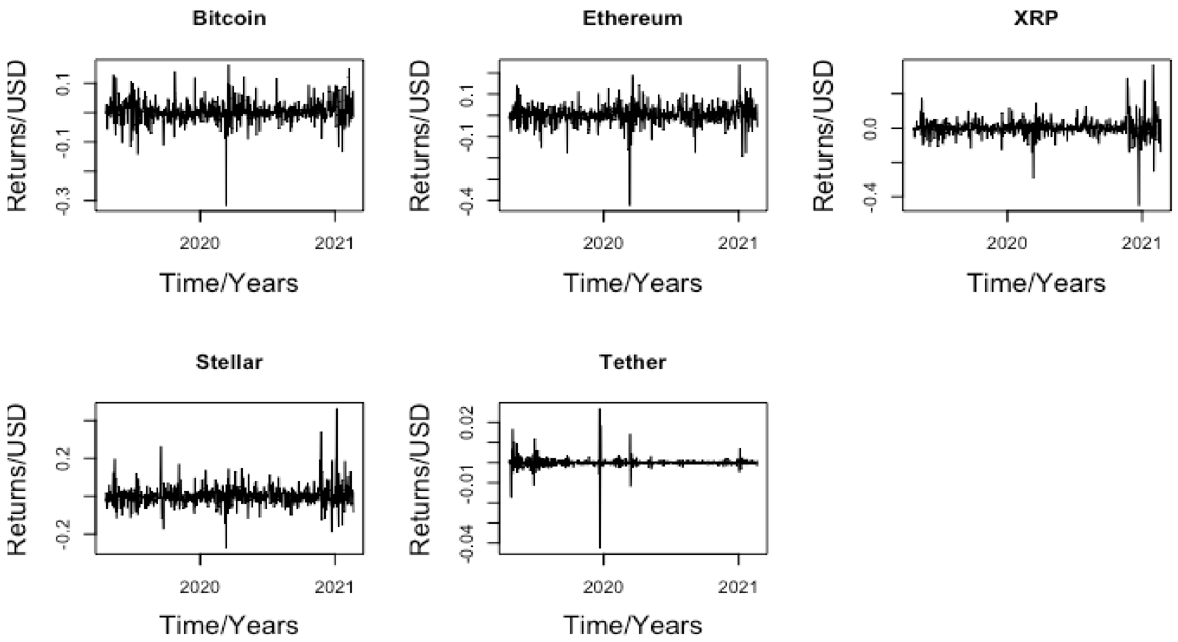


Table 1 shows the descriptive statistics for CSAD measure for daily data $CSAD_t$ and cap-weighted market return $r_{m,t}$ which is calculated using the market capitalisation of the selected cryptos. The normality tests (skewness and kurtosis) indicate that all the return series of the whole market and CSAD are non-normally distributed since the coefficient of skewness and kurtosis differ significantly from 0 and 3, respectively. This is further confirmed using the Jarque-Bera (JB) test statistics for normal distribution, which indicates the rejection of the null hypothesis of normal distribution of $CSAD_t$ and $r_{m,t}$ for the different market phases. The mean and standard deviation of $CSAD_t$and $r_{m,t}$ are very high during the COVID-19 period. These results possibly indicate that markets have atypical cross-sectional variations attributable to unanticipated events.

Table 1: Impact of public interest and COVID-19 milestones on Bitcoin futures trading

		No. Obs.	Mean	S.D.	Skewness	Kurtosis	JB Test
Total Period	$CSAD_{i,t}$	652	0.0141	0.0123	2.6898	13.2406	3635.10
	$r_{m,t}$	652	0.2659	3.7192	-0.9765	13.3110	2991.90
Pre COVID-19	$CSAD_{i,t}$	325	0.0257	0.0192	1.9500	7.8306	521.96
	$r_{m,t}$	325	0.0878	3.5051	-0.0618	5.3188	73.0180
During COVID-19	$CSAD_{i,t}$	327	0.0309	0.0286	2.6304	11.7790	1427.20
	$r_{m,t}$	327	0.4430	3.9178	-1.6526	18.5034	3423.7
Bear Market	$CSAD_{i,t}$	291	0.0279	0.0240	3.5328	23.4399	5671
	$r_{m,t}$	291	-2.5258	3.0267	-4.2438	35.3266	13544
Bull Market	$CSAD_{i,t}$	361	0.0280	0.0239	2.2532	9.2695	896.70
	$r_{m,t}$	361	2.5163	2.5011	1.8931	7.3205	496.42

3.2 Herding behaviour for the whole market period

Table 2 shows the regression results for the top 5 cryptos by market capitalisation for the total period under study. It can be observed that the coefficient of the variable r_{mt}^2 is negative ($\kappa_2 = -3.026\mathrm{e}-05$) at a 5% significance level. This suggests the existence of strong market-wide herding behaviour for the selected cryptos for the period under study. This means that during this period, investors trading in the top 5 cryptos followed the market's performance without adequate information and appreciation of the risk-reward trade-offs. That is to say, the distribution of the returns of the selected cryptos over the selected periods shrinks when the market returns experience a rise. This result is in congruence with the study of Bouri et al. (2019), Kaiser and Stöckl (2020), Ballis and Drakos (2020), Rubbaniy (2020), Yarovaya et al. (2021), among others who indicated the presence of herding behaviour on the crypto market but differs from the result of Stavroyiannis and Babalos (2019) who reported the absence of herding behaviour on the crypto market when ta time-varying regression model was used. As noted by Kaiser and Stöckl (2020), the presence of herding on the crypto market can be described by the influx of irrational investors in the predominantly traded cryptos like Bitcoin. It should, however, be noted that the presence of herding behaviour on the crypto market is to be overhauled, and the necessary correction may result in severe losses in wealth.

Table 2: Estimating regression coefficient of *CSAD*$_t$ on Equation 4

	Coeff.	S.E.	t-Stat	Prob
κ_0	7.014e-03	$6.134e-04$	11.435	<2e-16***
κ_1	2.996e-03	2.438e-04	12.290	<2e-16***
κ_2	-3.026e-05	1.395e-05	-2.169	0.0304*
R-Square	0.3352			
Adj. R-Square	0.3331			
F-Statistics	163.6			

Source: The Author, *** and * indicates significance at 1% and 5%, respectively

3.3. Herding behaviour for Pre Covid-19 and During Covid-19

Table 3 reports the regression result for the Pre Covid-19 and During Covid-19 period for the selected cryptos. The table shows that herding is present during the Covid-19 period as the regression coefficient is negative (κ_2 =-7.867e-05) and statistically significant at a 5% level. From this result, it can be stated, investors in the crypto market during the COVID-19 pandemic exhibit the tendency to mimic the trading decisions of other investors without exercising due diligence over the period of the study. The results also reflect the inefficiency in the crypto market during the COVID-19 pandemic, which produces a higher level of volatility. This result is consistent with the study in Rubbaniy (2020), which confirmed the presence of herding behaviour on the crypto market during the COVID-19 pandemic. However, this result stands in contrast to the result in Yarovaya et al. (2021), who concluded that COVID-19 do not heighten herd behaviour in cryptocurrency (crypto) markets during the COVID-19 pandemic. Yarovaya et al. (2021) results were based on small sample data from 1 January 2019 to 13 March 2020. It should be noted that COVID-19 was first detected in December 2019 and the World Health Organization (WHO) declared it a pandemic on 11 March 2020. Hence, their period of study for herding behaviour during the COVID-19 pandemic was about four months from the first date COVID-19 was observed, which might have accounted for the anti-herding behaviour of investors on the crypto market. This current study, however, employs a trading period from 1 December 2019 to 31 January 2021, which indicates a significant time period. The coefficient of r_{mt}^2 i.e., κ_2 for the Pre Covid-19 period is negative and not significant. However, to prove the existence of herding behaviour in a market, κ_2 must be negative and significant. Hence, herding is not present before the period Covid-19. The finding indicates that participants before the Covid-19 period made decisions rationally and did not follow the investment decisions of their peer investors. The R-squared values of 0.4032 and 0.3147 indicate that 40.31% and 31.48% of the variation on $CSAD_t$ can be explained by daily market returns and their square term.

Table 3: Regression Results for Pre COVID-19 and During COVID-19

Variable	Pre- COVID-19				During COVID-19			
	Coeff	S. E.	t-Stat	Prob	Coeff	S. E.	t-Stat	Prob
κ_0	1.193e-02	1.568e-03	7.606	3.14e-13***	1.550e-02	1.989e-03	7.7950	8.85e-14***
κ_1	5.964e-03	8.889e-04	6.709	8.82e-11***	6.564e-03	7.618e-04	8.6160	3.10e-16***
κ_2	-1.011e-04	8.507e-05	-1.189	0.2350	-7.867e-05	3.667e-05	-2.1450	0.0327*
R-Square	0.4032				0.3147			
Adj. R-Square	0.3995				0.3104			
F-Statistics	108.8				74.38			

Source: The Author, *** and * indicates significance at 1% and 5%, respectively

3.4. Herding behaviour for the bull and bear markets (Asymmetry in herding behaviour)

This section gives empirical results on whether crypto herding exhibits distinct behaviours under different market trends. The total period is divided into two sub-periods using the index returns, that is, negative and positive index returns. Table 4 presents the outcomes of the tests for herding behaviour in the bull (positive returns) and bear (negative returns) market. The results in the table indicate the existence of herding asymmetry in the trading behaviour of investors in the crypto market as herding during the days of positive market returns are significantly higher than the days of negative market returns of the selected crypto's. The finding is consistent with the study of Rubbaniy (2020), Stavroyiannis and Babalos (2019), and Ballis and Drakos (2020). Also, as seen in the table, the negative coefficients of the market return for the bull (κ_2 = -0.0003) and bear (κ_2 = -9.799e-06) market suggest the presence of herding in both markets. However, the latter coefficient is not statistically significant. For this reason, it can be concluded that herding only exists in the bull market. That is, at periods when the prices of cryptos are steadily increasing, investors trading in the top 5 cryptos are inclined to behave similarly.

Table 4: Regression Results for Bull and Bear market

Variable	Bull Market				Bear Market			
	Coeff	S.E	t-Stat	Prob	Coeff	S. E.	t-Stat	Prob
κ_0	0.0114	0.0019	5.9580	6.12e-09***	1.479e-02	1.665e-03	8.8840	<2e-16***
κ_1	0.0080	0.0011	7.4930	5.34e-13***	5.249e-03	6.383e-04	8.2240	6.82e-15***
κ_2	-0.0003	0.0001	-2.7630	0.00602**	-9.799e-06	2.949e-05	-0.3320	0.74
R-Square	0.3204				0.4084			
Adj. R-Square	0.3166				0.4043			
F-Statistics	84.38				99.42			

Source: The Author, *** and * indicates significance at 1% and 5%, respectively

4. Conclusion

In this paper, we study the trading behaviour for the five largest cryptocurrencies based on their market capitalisation from 20 April 2019, to 31 January 2021, for four distinct sub-periods (Pre and during the COVID-19 period, bear, and bull market). To empirically test for herd behaviour in all the sub-periods, the dispersion model of Chang et al. (2000) is used. The results using the model show evidence of herd behaviour for the entire period under study. We also find evidence that the COVID-19 pandemic increases herd behaviour in the cryptocurrency market. There was also evidence of herd behaviour in the bullish market.

The existence of herding behaviour in the whole market period, bullish market, and during Covid-19 indicates the inefficiency in the market and generates a higher level of risk and volatility. The study is significant to investors, market regulators, and policymakers in the cryptocurrency market to deepen their understanding of herding behaviour during market crisis periods like the COVID-19 pandemic.

Declarations:

Availability of data
Data for this work is available from the corresponding author upon request.

Competing Interest
The author declares that they have no competing interests.

Funding
This work did not receive any funding.

References

Andrada-Félix, J., Fernandez-Perez, A., Sosvilla-Rivero, S., 2020. Distant or close cousins: Connectedness between cryptocurrencies and traditional currencies volatilities. Journal of International Financial Markets, Institutions and Money 67, 101219.

Associated Press, 2020. Timeline of key events in the spread of the new coronavirus Associated Press, available at: https://apnews.com/article/f143c90d86e5887fbb74cdc40b6796da (accessed 10 September 2020)

Baig, A. S., Haroon, O., Sabah, N., 2020. Price Clustering After the Introduction of Bitcoin Futures. Applied Finance Letters, 9, 36 - 42.

Bauer, D., Dimpfl, T., 2019. Price discovery in bitcoin spot or futures? Journal of Futures Markets 39, 803-817

Baur, D., Hoang, L., 2021. A crypto safe haven against Bitcoin. Finance Research Letters, 101431.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters 20, 192-198.

CNN Editorial Research (2020), "Coronavirus Outbreak Timeline Fast Facts", CNN, 7 September, available at: https://www.cnn.com/2020/02/06/health/wuhan-coronavirus-timeline-fast-facts/index.html (accessed 10 September, 2020)

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., Oxley, L., 2020. Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. Economics Letters 194, 109377.

Corbet, S., Larkin, C., Lucey, B., 2020. The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. Finance Research Letters 35, 101554.

Corbet, S., Lucey, B., Maurice, P. and Samuel, V. (2018), "Bitcoin Futures—What use are they?", Economics Letters, Vol. 172, pp. 23-27.

Federal Reserve Bank of St. Louis. (2020), "Timeline of Events Related to the COVID-19 Pandemic", Federal Reserve Bank of St. Louis, available at: https://fraser.stlouisfed.org/timeline/covid-19-pandemic (accessed 10 September, 2020)

Jia, J., & Kang, S. B. (2021). Do the basis and other predictors of futures return also predict spot return with the same signs and magnitudes? Evidence from the LME. Journal of Commodity Markets, 100187.

Karalevicius, V., Degrande, N., De Weerdt, J., 2018. Using sentiment analysis to predict interday Bitcoin price movements. Journal of Risk Finance 19, 56-75.

Kim, S. T., 2021. Is it worth to hold Bitcoin?, Finance Research Letters, 102090.

Philippas, D., Rjiba, H, Guesmi, K., Goutte, S., 2019. Media attention and Bitcoin prices. Finance Research Letters, 37-43.

Reuters staff, Editing by de Kretser, L., Wu, T., 2020. Timeline: How the global coronavirus pandemic unfolded, Reuters, 28 June, available at: https://www.reuters.com/article/us-health-coronavirus-timeline/timeline-how-the-global-coronavirus-pandemic-unfolded-idUSKBN23Z0UW (accessed September 10, 2020)

Smales, L.A., 2019. Bitcoin as a safe haven: is it even worth considering? Finance Research Letters 30, 385–393

Taylor, D.B., 2020. A Timeline of the Coronavirus Pandemic. New York Times, 6 August, available at: https://www.nytimes.com/article/coronavirus-timeline.html (accessed 10 September, 2020)

World Health Organization (WHO), 2020. Timeline of WHO's response to COVID-19. World Health Organization, available at: https://www.who.int/news-room/detail/29-06-2020-covidtimeline (accessed 30 June, 2020)

APPLIED FINANCE LETTERS

VOLUME 10, 2021

INVESTOR ATTENTION AND HERDING IN THE CRYPTOCURRENCY MARKET DURING THE COVID-19 PANDEMIC

Hajam Abid Bashir[1*], Dilip Kumar[1], K Shiljas[1]

1. Finance and Accounting, Indian Institute of Management Kashipur, Uttrakhand, India

* Corresponding Author: Hajam Abid Bashir, Finance and Accounting, Indian Institute of Management Kashipur, Uttrakhand, India, ✉ hajam.fpm1705@iimkashipur.ac.in

Abstract

This study examines the relationship between investor attention and herding effect in the cryptocurrency market by employing the vector autoregression and quantile regression models. Furthermore, we examine whether the COVID-19 pandemic affected herding behaviour in cryptocurrencies. Using the daily closing price and Google search volume of the five leading cryptocurrencies, the paper finds that herding in the cryptocurrency market decreases with an increase in investor attention for the overall sample. The results for the COVID-19 period indicate that the impact of investor attention on the herding effect decreases due to increased attention to the pandemic. This study is one of the initial attempts to investigate the impact of investor attention on herding in cryptocurrencies.

Keywords: Investor attention, Herding, Cryptocurrency market, Coronavirus, COVID-19.

1. Introduction

The rapid spread of COVID-19, which is considered the third deadliest virus surge within the past 20 years period (Yang et al., 2020), led to a lot of havoc worldwide. As the COVID-19 outbreak resulted in disruptions in the equity and commodity markets across the globe with a declining trend in prices and a great level of uncertainty (Gupta et al., 2021), cryptocurrency markets also witnessed similar disturbances during 2020 (Naeem et al., 2021). Literature also highlights that the markets across the globe have not experienced such extreme volatile movements in prices in the past (Zhang et al., 2020; Haroon and Rizvi, 2020).

There exists a notion among investors about the hedging ability of Bitcoin during the downturn in the market (Dyhrberg, 2016). In the initial stage of the COVID-19 outbreak, investors considered Bitcoin as a hedging instrument which later resulted in more depletion in value than other assets. Most of the latest studies have looked into the damage caused by the COVID-19 crisis in the cryptocurrency market (James et al., 2021; Conlon et al., 2020). Bitcoin was found to have an amplifying impact on global financial markets rather than acting as a tool of diversification during this COVID-19 outbreak (Corbet et al., 2020; Conlon and McGee, 2020; Conlon et al., 2020). The cryptocurrency market has been negatively affected by the COVID-19 outbreak, diminishing its use as a diversification tool (Conlon and McGee, 2020).

The news related to the sudden increase in COVID-19 cases created an environment of uncertainty and resulted in a surge in panic and fear among the public (Salisu and Vo, 2020; Fernandez-Perez et al., 2020). With the increase in COVID-19 cases, investors searched for more details of the coronavirus on the internet (Lyócsa et al.,2020). Market participants face difficulty in making a concrete understanding of such information when exposed to a ton of news from varied sources. Barberis et al. (1998) postulate with psychological evidence that the market overreacts to such outpouring of news, although less weight should be given to this news.

Bikhchandani et al. (1992) and Sgroi (2002) point out that if there is a low-cost associated with the search of information, investors will have the incentive to gain information and exhibit herding behaviour. Herding results from the movement of a set of investors' actions towards a particular direction by mimicking a few participants' behaviour. Theoretical literature has explained the interconnection between information and herd mentality (Sias, 2004; Nofsinger and Sias, 1999; Shleifer and Summers, 1990). Herding stems from the psychological biases of individuals and the phenomena of attention-seeking factors (Barber et al., 2009; Li et al., 2017).

There is a wide range of studies on herding behavior in the cryptocurrency market (Bouri et al., 2019; Vidal-Tomás et al., 2019). The Cryptocurrency market is characterised by the absence of proper legal structure and unavailability of adequate standard information (Ji et al., 2019). Less knowledgeable individuals use this information to trade in the cryptocurrency market without adequately comprehending the risk associated with such a venture. In most cases, they are driven by other participants' characteristics and actions in the market, making them exhibit herd mentality, which becomes more severe during turbulence and uncertain times (Naeem et al., 2021).

Analysing the herd mentality in the cryptocurrency market helps bring out valuable insights regarding the price variations (Corbet et al., 2019) and provides information regarding the connectedness and integration among the cryptocurrencies. However, the absence of strict fundamentals in proper valuation, along with the constant exposure of investors towards social networking sites, makes the cryptocurrency market vulnerable to an examination of behavioural aspects of investor actions (Corbet et al., 2019).

Several studies document the vulnerability of the cryptocurrency market towards behavioural elements such as sentiment from both media and markets (Weber, 2014), noise trading (Cheung et al., 2015; Fry and Cheah, 2016), and speculative bubbles (Cheah and Fry, 2015). However, Bouri et al. (2019) note that herd mentality is a time-varying phenomenon, and the market participants tend to base their decision on the performance of larger digital currencies as the smaller ones tend to follow the pattern of large cryptocurrencies (Vidal-Tomás et al., 2019).

Kahneman's (1973) proposition regarding the attention phenomenon highlights that it is a cognitive instinct that propels the decision to purchase an asset and can be considered as the linking element that explains the relation between media attention and bitcoin transactions. The concern of cognitive limitation (Kahneman, 1973) for investor attention has a far-reaching impact in the booming arena of virtual social networking and when there is larger uncertainty prevailing in the COVID-19 scenario around the globe.

Typically, "investor attention" is all about one's conscious awareness about the reality of a kind of information relating to something. Google search volume is proxied for investor attention in many of the studies. Studies show that asset values get impacted by investor attention, and there is variation in its character with respect to time (Da et al., 2011). Prominent incorporation of news into asset prices is evident when market participants pay greater attention to the news, and it gets reflected in the prices (Huberman and Regev, 2001).

The relationship between investor attention and bitcoin is being studied using various proxies under multiple settings (Shen et al., 2019; Figa-Talamanca and Patacca, 2019; Dastgir et al., 2019). Within the sphere of our knowledge, there does not exist any study exploring the relationship between investor attention and herding behaviour in the cryptocurrency market. Therefore, we attempt to delve into the underlying variations in the cryptocurrency market's behaviour before the COVID-19 and how it got evolved along with the market turbulence in the pandemic. This study examines the relationship between investor attention and herding effect in the cryptocurrency market from August 7, 2015, to November 23, 2020, with a particular focus on the COVID-19 outbreak. We test the relationship between investor attention and herding effects across the entire period and two different regimes: the period before the COVID-19 outbreak (from August 7, 2015 to January 14, 2020) and the period after the COVID-19 outbreak (from January 15, 2020 to November 23, 2020). This helps us to distinguish the differences in investor attention on herding in cryptocurrencies across two distinct sentiment periods. Our study is one of the initial attempts to investigate the impact of investor attention on herding in cryptocurrencies. We use Google search volume as a proxy for investor attention, which acts as a free information source and measures investors' attention propensity.

The remainder of the paper is structured as follows. Section two discusses the data and methodology. Section three presents empirical results and some discussions, and Section four concludes the paper.

2. Data and Methodology

2.1 Cryptocurrency Data

We use the daily data of five major cryptocurrencies based on the market capitalization as of November 23, 2020. The prices of all cryptocurrencies (denominated in USD) are obtained from investing.com. The data span from August 7, 2015, to November 23, 2020. Table 1 reports the total market capitalization of cryptocurrencies. Bitcoin dominates the market with a share of 61.7%, followed by Ethereum (11.69%), Ripple (5.27%), Tether (3.27%), and Litecoin (0.99%). These cryptocurrencies account for 82.92% of the total market capitalization.

Table 1: The Market capitalization of cryptocurrencies

Name	Symbol	Market capt	Share
Bitcoin	BTC	3,52,39,37,69,773	61.71%
Ethereum	ETH	66,73,71,16,945	11.69%
Ripple	XRP	30,10,19,22,821	5.27%
Tether	USDT	18,66,76,90,992	3.27%
Litecoin	LTC	5,67,06,53,476	0.99%
The total market capitalization of the cryptocurrency market: $5,71,06,11,12,332			

2.2 Google Search Volume

We use Google search volume index (GSVI) as a proxy for investor attention obtained via Google Trends. It provides a time series of the volume of search queries. Google Trends provides the term-specific index that directly relates to the sentiment of google users. We use the following search keywords: 'Bitcoin,' 'Ethereum,' 'Litecoin,' 'XRP' (for Ripple), and 'USDT' (for Tether). The daily GSVI is obtained using a 3-month window. To avoid the possibility of unrelated noise in the search data, we employ the precise keyword for each cryptocurrency to capture only relevant information. Finally, to measure the aggregate investor attention, we take the average value by utilizing the daily GSVI of all the cryptocurrencies. Following Lin

(2021) and Baig et al. (2019) we scale the aggregate investor attention by 100 as shown below:

$$GSV_t = \frac{\left(\frac{1}{N}\left(\sum_{i=1}^{5} GSVI_{i,t}\right)\right)}{100} \tag{1}$$

GSV_t is the aggregate investor attention at time *t*; N is the number of cryptocurrencies and $GSVI_{i,t}$ is the Google search volume index for cryptocurrency *i* at time *t*.

2.3 Herding calculation method

In this study, we apply the Cross-Sectional Absolute Deviation (CSAD) method proposed by Chang et al. (2000) to measure the presence of herding in the cryptocurrency market. The CSAD statistic is measured as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{2}$$

Where $R_{i,t}$ is the return of cryptocurrency i on day t and $R_{m,t}$ is the market return on day t. We use Cryptocurrency Index (CRIX) as a proxy for the market index, the data of which is obtained from http://data.thecrix.de.

Chang et al. (2000) argued that during extreme market movements (when the market is under stress), the relationship between CSAD and market return ($R_{m,t}$) is expected to be non-linear. If investors mimic each other during the market stress period, the CSAD decreases, which turns the relation between the square of market return and CSAD negative. The negative relation between the square of market return and CSAD is an indication of herding. The same is shown in the following equation:

$$CSAD_t = \alpha_0 + \beta_1|R_{m,t}| + \beta_2 R^2{}_{m,t} + \varepsilon_t \tag{3}$$

The presence of herding behaviour is tested as:

a) If $\beta_1 > 0$ *and* $\beta_2 = 0$, it means there is an absence of herding.
b) If $\beta_2 < 0$ and significant, it means herding behaviour exists.
c) If $\beta_2 > 0$, and significant it means anti-herding behaviour exists.

Table 2 shows the descriptive statistics and the stylized facts of investor attention (GSV) and herding effect (CSAD). We can see that the mean value of CSAD and GSV has increased during the COVID-19 period. Furthermore, CSAD shows significant variation during the COVID-19 ranging from 0.004 to 0.558 with a standard deviation of 0.045. Similarly, GSV varies in the range of 0.212 to 0.868 with a standard deviation of 0.132. For stylized facts, we report the JB (Jarque-Bera) test for normality test and ADF (Augmented Dickey-Fuller) test to investigate the stationarity. The results indicate that CSAD and GSV are positively skewed and non-normally distributed. The ADF test statistic shows that all the given series are stationary.

Table 2: Descriptive Statistics

	Whole-sample		Pre-COVID-19		COVID-19 period	
	CSAD	GSV	CSAD	GSV	CSAD	GSV
Mean	0.035	0.421	0.035	0.417	0.037	0.448
Median	0.025	0. 42	0.025	0.418	0.025	0.426
Minimum	0.0008	0.10	0.001	0.100	0.004	0.212
Maximum	0.558	0.922	0.305	0.922	0.558	0.868
Std dev	0.0349	0.0135	0.033	0.136	0.045	0.132
Skewness	4.022	0.255	2.486	0.161	6.550	0.851
Kurtosis	36.238	0.297	9.798	0.192	64.372	0.449
Jarque-Bera	110526.9	28.009	8106	9.416	54701	39.839
ADF	-10.369 **	-6.413 **	-5.876 **	-5.114 **	-6.607 **	-6.607 **

This table reports the descriptive statistics of the herding effect and investor attention. CSAD stands for Cross-Sectional Absolute Deviation; GSV stands for Google search volume. ADF test for the Augmented Dickey-Fuller test. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-COVID-19 (from August 7, 2015, to January 14, 2020) and COVID-19 period (from January 15, 2020, to November 23, 2020). ** denotes significance at 1% level.

2.4 Vector autoregression (VAR) model

To analyze the relationship between herding effects and investor attention, we consider the following Vector autoregression (VAR) models:

$$(CSAD_t) = \alpha_0 + \sum_{f=1}^{T} \beta_f(CSAD_{t-f}) + \sum_{r=1}^{T} \beta_r(GSV_{t-r}) + e_t \tag{4}$$

$$(GSV_t) = \alpha_0 + \sum_{f=1}^{T} \beta_f(CSAD_{t-f}) + \sum_{r=1}^{T} \beta_r(GSV_{t-r}) + e_t \tag{5}$$

where $CSAD_t$ is the herding statistic in cryptocurrencies at time *t*; GSV_t is the investor attention at time *t* and e_t is the error term. *T* represents the lag length. We use Schwarz Information Criterion (SIC) to obtain the optimal lag lengths.

3. Empirical Results

Table 3 reports the results of equation (3). We can see that the values of β_1 and β_2 are positive and significant for the whole sample and the COVID-19 period. This infers that there is anti-herding behaviour in the cryptocurrency market. These results are in line with Coskun et al. (2020), which shows evidence of anti-herding in the cryptocurrency market. This anti-herding behaviour can be attributed to the increased presence of informed traders in the cryptocurrency market preceding the occurrence of uncertain events (Feng et al., 2018; Yarovaya et al., 2021). We report the vector autoregression estimates for investor attention and herding in Table 4. The 2nd and 3rd columns report the results for the whole sample period. The results for CSAD as the dependent variables show that investor attention has a one-day lagged positive effect on CSAD and that there is no effect for the second and third lag of investor attention. The results indicate that the anti-herding effect increases in the short run with increased investor attention. From our findings, it appears that increased investor attention can eventually increase the price efficiency in the cryptocurrency market as investors are able to process more cryptocurrency specific information on their own, which can alleviate herding effects. These findings add to the literature of information discovery aspect of investor attention (Vlastakis and Markellos, 2012)

Table 3: Results of CSAD on Market Return

	Whole sample		Pre-Covid		Covid period	
Parameter	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
α_0	0.018 **	0.0017	0.016 **	0.001	0.018 **	0.0025
β_1	0.612 **	0.060	0.785 **	0.079	0.724 **	0.069
β_2	0.993 *	0.410	-0.690	0.824	1.093 **	0.149
Adj. R^2	0.453		0.412		0.600	

This table shows the results of equation (2). The sample period of the analysis is from August 7, 2015, to November 23, 2020, with 1936 observations. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-Covid (from August 7, 2015, to January 14, 2020) and Covid period (from January 15, 2020, to November 23, 2020). ** denotes significance at 1% level.

Table 4: Results of the VAR model

	Whole sample		Pre-COVID-19		COVID-19 period	
	CSAD	**GSV**	**CSAD**	**GSV**	**CSAD**	**GSV**
Constant	0.015 ** (0.001)	0.019 ** (0.006)	0.014 ** (0.001)	0.022 ** (0.008)	0.015 ** (0.005)	0.015 (0.011)
CSAD (-1)	0.486 ** (0.079)	0.174 (0.149)	0.417 ** (0.034)	0.172 (0.185)	0.743 ** (0.229)	0.290 (0.229)
CSAD (-2)	−0.086 * (0.048)	−0.480 ** (0.160)	0.000 (0.035)	−0.446 * (0.191)	−0.423 * (0.183)	−0.634 * (0.258)
CSAD (-3)	0.183 ** (0.031)	−0.242 (0.154)	0.173 ** (0.032)	−0.354 * (0.176)	0.291 ** (0.108)	0.048 (0.197)
GSV (-1)	0.018 ** (0.004)	−0.348 ** (0.034)	0.017 ** (0.004)	−0.340 ** (0.037)	0.026 ** (0.010)	−0.425 ** (0.058)
GSV (-2)	0.001 (0.004)	−0.231 ** (0.029)	0.004 (0.004)	−0.225 * (0.032)	−0.013 (0.012)	−0.287 ** (0.051)
GSV (-3)	−0.000 (0.004)	−0.119 ** (0.021)	−0.002 (0.003)	−0.113 ** (0.023)	0.031 * (0.014)	−0.171 ** (0.054)
Adj. R^2	0.276	0.125	0.250	0.110	0.40	0.170

This table presents the VAR model results with herding effect (CSAD) and investor attention (GSV) as a dependent variable. The standard errors are reported in parentheses. We use Schwarz Information Criterion (SIC) to obtain the optimal lag lengths. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-COVID-19 (from August 7, 2015, to January 14, 2020) and COVID-19 period (from January 15, 2020, to November 23, 2020). ** and * denotes significance at 1% level and 5% level, respectively.

To investigate the impact of investor attention on herding during the COVID-19 pandemic, we divide our sample into two periods. The pre-COVID-19 period from August 7, 2015, to January 14, 2020, and the COVID-19 period from January 15, 2020, to November 23, 2020. The COVID-19 period is chosen from January 15, 2020, as the first confirmed case of COVID-19 was detected outside China on January 14, 2020, based on WHO Disease Outbreak News. Results are shown in Columns 4-7 of Table 4. The results indicate a positive effect of investor attention on anti-herding in both regimes; however, the difference in the magnitude of the coefficients indicates that the impact is more prevalent in the COVID-19 period. Also, there is a three-day lagged positive effect of investor attention on CSAD during the COVID-19 period. The strong relation during the COVID-19 period is not an unexpected result as investors paid more attention to cryptocurrencies during the ongoing pandemic (Chen et al., 2020). Our results are in line with the findings of Yarovaya et al. (2021), which claims that herding in the cryptocurrency market decreased during the COVID-19 pandemic.

3.1 Additional Analysis

There is a possibility that during the COVID-19 period, the herding is influenced directly by the spread of coronavirus. We, therefore, perform an additional analysis using "coronavirus" as a search keyword. We obtain a daily Google search volume index of the keyword "coronavirus" from Google trends globally from January 15, 2020, to November 23, 2020. Table 5 reports the results of the VAR model for the herding effect and investor attention. The estimated coefficients show that investor attention on "coronavirus" is positively related to the anti-herding in cryptocurrencies in the short run, indicating a temporal effect that balanced out in two days.

Table 5: "Coronavirus" search volume and herding effect in cryptocurrencies.

	Constant	CSAD (-1)	CSAD (-2)	CSAD (-3)	GSV (-1)	GSV (-2)	GSV (-3)	*Adj. R^2*
CSAD	0.013 **	0.581 **	−0.296 *	0.115	0.383 *	-0.366	0.0269	0.458
	(0.004)	(0.144)	(0.124)	(0.093)	(0.188)	(0.205)	(0.099)	
GSV	0.002	-0.197 *	0.284 **	−0.042	1.154 **	−0.142	−0.030	0.977
	(0.002)	(0.837)	(0.086)	(0.050)	(0.113)	(0.114)	(0.1031)	

This table shows the VAR results of the herding effect (CSAD) and investor attention (GSV), where GSV is the Google search volume of the "coronavirus" keyword at the global level. The standard errors are reported in parentheses. The sample period is from January 15, 2020, to November 23, 2020. ** and * denotes significance at 1% level and 5% level, respectively.

Furthermore, we run quantile regression to model the herding effect as a function of various quantiles of investor attention. We provide the results in Table 6. According to the results, all the coefficients are positive and significant at a 1% level. However, the greatest effect is observed for the 95th% and 90th% quantiles for $GSV_{(t)}$ and 80th% and 90th% quantiles for $GSV_{(t-1)}$. The results indicate that an increase in GSV will lead to an increase in CSAD. We also report the test of differences in coefficient across the quantiles (Q1, Q4, Q6, A9, and Q11). The evidence shows significant differences in the coefficients, indicating heterogeneity in the relationship between investor attention and CSAD across different quantiles.

Table 6: Quantile regression results

Regression results			Differences of coefficients across quantiles		
Quantiles	**GSV**	**GSV (-1)**	**Quantiles**	**GSV**	**GSV (-1)**
Q1 (0.05)	0.01 **	0.005 **	Q1-Q4	-0.018 **	-0.014 **
Q2 (0.10)	0.012 **	0.007 **	Q1-Q6	-0.034 **	-0.027 **
Q3 (0.20)	0.02 **	0.017 **	Q1-Q9	-0.057 **	-0.058 **
Q4 (0.30)	0.028 **	0.019 **	Q1-Q11	-0.064 **	-0.055 *
Q5 (0.40)	0.033 **	0.023 **	Q4-Q6	-0.016 **	-0.013 *
Q6 (0.50)	0.044 **	0.032 **	Q4-Q9	-0.039 **	-0.044 **
Q7 (0.60)	0.051 **	0.042 **	Q4-Q11	-0.046	-0.041
Q8 (0.70)	0.055 **	0.051 **	Q6-Q9	-0.023 *	-0.031 **
Q9 (0.80)	0.067 **	0.063 **	Q6-Q11	-0.030	-0.028
Q10 (0.90)	0.083 **	0.064 **	Q9-Q11	-0.007	0.003
Q11 (0.95)	0.074 **	0.060 **			

This table presents quantile regression results with the herding effect (CSAD) as a dependent variable for the whole sample period (August 7, 2015, to November 23, 2020). The regression equation is $CSAD_{(\delta)t} = \alpha_{(\delta)0} + \lambda_{(\delta)}GSV_{(t)}$ *and* $CSAD_{(\delta)t} = \alpha_{(\delta)0} + \lambda_{(\delta)}GSV_{(t-1)}$. δ represents different quantiles. Columns five and six show the differences of coefficients across quantiles (0.05,0.30,0.50,0.80, and 0.95). ** and * denotes significance at 1% level and 5% level, respectively.

4. Conclusion

This study explores the relationship between investor attention and herding behaviour, one of the prominent behavioural characteristics evident among investors. The period of uncertainty confronted in the COVID-19 outbreak opens a scenario to look at this relationship in the cryptocurrency market. Academic literature underlines that where there is low inertia in the information acquisition process, individuals obtain information from various sources and tend to show herd mentality (Bikhchandani et al., 1992; Sgroi, 2002).

Our study is one of the initial attempts to examine the impact of investor attention on herding in cryptocurrencies. We use the Google search volume index as a proxy for investor attention, which acts as a free information source and measures investors' attention propensity. Our study shows important findings on herd mentality in the cryptocurrency market. The overall sample results show a positive effect of investor attention on anti-herding in the cryptocurrency market. According to sub-period analysis, the results indicate a positive effect of investor attention on anti-herding behaviour in both periods. However, the difference in the magnitude of the coefficients suggests that the impact is more prevalent in the COVID-19 period. During the current COVID-19 outbreak, there is a greater exertion of information regarding the market operation stemming from individual investors' greater attention.

References

Baig, A., Blau, B. M., & Sabah, N. (2019). Price clustering and sentiment in bitcoin. *Finance Research Letters, 29*, 111-116.

Barber, B. M., Odean, T., & Zhu, N. (2009). Systematic noise. *Journal of Financial Markets*, *12*(4), 547-569.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics, 49(3)*, 307-343.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992-1026.

Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, *29*, 216-221.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), 1651-1679.

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics letters*, *130*, 32-36.

Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and bitcoin price dynamics: The case of COVID-19. Emerging Markets Finance and Trade, 56(10), 2298-2309.

Cheung, A., Roca, E., & Su, J. J. (2015). Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, *47*(23), 2348-2358.

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Finance Research Letters, 35, 101607.

Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*, *54*, 101248.

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., & Oxley, L. (2020). Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. *Economics Letters*, *194*, 109377.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, 101554.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182-199.

Coskun, E. A., Lau, C. K. M., & Kahyaoglu, H. (2020). Uncertainty and herding behavior: Evidence from cryptocurrencies. Research in International Business and Finance, 54, 101284.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461-1499.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., & Lau, C. K. M. (2019). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters*, *28*, 160-164.

Donadelli, M., Kizys, R., & Riedel, M. (2017). Dangerous infectious diseases: Bad news for Main Street, good news for Wall Street?. *Journal of Financial Markets*, *35*, 84-103..

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters*, *16*, 85-92.

Feng, W., Wang, Y., & Zhang, Z. (2018). Informed trading in the Bitcoin market. Finance Research Letters, 26, 63–70.

Fernandez-Perez, A., Gilbert, A., Indriawan, I., & Nguyen, N. H. (2021). COVID-19 pandemic and stock market response: A culture effect. *Journal of Behavioral and Experimental Finance*, 29, 100454.

Figa-Talamanca, G., & Patacca, M. (2019). Does market attention affect Bitcoin returns and volatility?. *Decisions in Economics and Finance*, *42*(1), 135-155.

Fry, J., & Cheah, E. T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, *47*, 343-352.

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, *164*, 109-111.

Gupta, R., Subramaniam, S., Bouri, E., & Ji, Q. (2021). Infectious disease-related uncertainty and the safe-haven characteristic of US treasury securities. *International Review of Economics & Finance*, *71*, 289-298.

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, *27*, 100343.

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *The Journal of Finance*, *56*(1), 387-396.

James, N., Menzies, M., & Chan, J. (2021). Changes to the extreme and erratic behaviour of cryptocurrencies during COVID-19. *Physica A: Statistical Mechanics and its Applications, 565,* 125581.

Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, *63*, 257-272.

Kahneman, D. (1973). *Attention and effort* (Vol. 1063, pp. 218-226). Englewood Cliffs, NJ: Prentice-Hall.

Li, W., Rhee, G., & Wang, S. S. (2017). Differences in herding: Individual vs. institutional investors. *Pacific-Basin Finance Journal*, *45*, 174-185.

Lin, Z. Y. (2021). Investor attention and cryptocurrency performance. *Finance Research Letters, 40,* 101702.

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance research letters*, *36*, 101735.

Naeem, M. A., Bouri, E., Peng, Z., Shahzad, S. J. H., & Vo, X. V. (2021). Asymmetric efficiency of cryptocurrencies during COVID19. *Physica A: Statistical Mechanics and its Applications*, *565*, 125562.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of finance*, *54*(6), 2263-2295.

Phillip, A., Chan, J. S., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, *163*, 6-9.

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis*, *71*, 101546.

Sgroi, D. (2002). Optimizing information in the herd: Guinea pigs, profits, and welfare. *Games and Economic Behavior*, 39(1), 137-166.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict Bitcoin?. *Economics Letters*, *174*, 118-122.

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic perspectives*, *4*(2), 19-33.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies*, *17*(1), 165-206.

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance Research Letters*, *30*, 181-186.

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance, 36(6),* 1808-1821.

Weber, B. (2016). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics*, *40*(1), 17-41.

Yang, Y., Peng, F., Wang, R., Guan, K., Jiang, T., Xu, G., ... & Chang, C. (2020). The deadly coronaviruses: The 2003 SARS pandemic and the 2020 novel coronavirus epidemic in China. *Journal of autoimmunity*, *109*, 102434.

Yarovaya, L., Matkovskyy, R., & Jalan, A. (2021). The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money,* 101321.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

COVID-19 IS DEADLY! LONG LIVE THE KING, CORPORATE CASH HOLDINGS!

Akanksha Saxena[1], R. Ranajee[1*], Ms Saumita Roy[1]

1. ICFAI Business School, Hyderabad, India

* Corresponding Author: Ranajee Ranajee, Associate Professor, ICFAI Business School, Hyderabad, India, ✉ Email: ranajee@ibsindia.org

Abstract

COVID-19 has adversely affected the human race. With the human race confined to their houses, the level of consumption has gone down and it has a significant negative impact on the cash flows of the existing businesses. In this study, using different scenarios and stress levels, we try to predict the impact of COVID-19 on a business's cash flows and establish the role of corporate cash holdings in avoiding the illiquidity of businesses.

Keywords: COVID-19, Illiquidity, Cash crunch, Stress test, Debt structure

1. Introduction

Corporate cash holding is a tradeoff between liquidity and investment. Cash is the basis of the sustenance of a business. Excess cash provides liquidity in times of external externalities. It also eliminates the underinvestment problem. The lower level of cash leads to costly external financing for the investment (Habib and Hasan, 2017; Al-dhamari et al., 2015). Holding cash is connected to efficiency gains where businesses with valuable investment ventures and businesses with greater cash flow risks are expected to hold more cash. Holding cash offers liquidity with the flexibility to the businesses (Keynes, 1934), however, it is also regarded as pervasive in nature (Kalcheva and Lins, 2007; Pinkowitz et al., 2012). Researchers have empirically tested and validated the commonly held intentions of firm cash holdings (Baumol, 1952; Mulligan, 1997; Opler et al., 1999; Harford, 1999), its diverse determinants (Ferriera and Vilela, 2004; Chen and Chuang, 2009; Duchin, 2010; Al-Najjar, 2013), and reported an increasing trend in corporate cash holdings.

Irrelevance theory (Keynes, 1934), asserts that investment and financing are distinct decisions and are not affected by each other. So, in a perfect market situation, corporate cash holding should not matter. On the contrary, pecking order theory (Myers and Majluf, 1984) postulates a sequencing in the financing of the projects. The internally generated cash is followed by debt and finally equity. Financing in pecking order theory follows the cost of financing from lowest to highest. Investments by the company and its growth are limited by internal sources of funding during the credit crunch. Small companies have more information asymmetry about their growth assets, and they are financially inadequate. The role of corporate cash holdings becomes important during the time of credit crunch or to such companies (Denis and Sibilkov, 2009). Bates et al., 2009 report the significance of cash holdings, during the economic crisis. External capital market or bank funding becomes challenging during the financial crisis due to the deficit of confidence. Usable cash holding becomes a defence against external instability in the macroeconomic climate.

Based on the above arguments and pieces of evidence, it is important, for investors, to monitor the cash available to a company, its capital expenditure, and its cash flow levels before making an investment decision. Cash use analysis tells investors till what time a business is self-sustaining. Investors also need to pay attention to the cash burn rate of a company. Cash burn rate refers to the rate at which businesses absorb the money supply over time. A high-burn business will find itself scurrying for cash from banks or creditors. In order to minimize the cash burn rate and avoid the fate of running out of cash, the businesses should either reduce costs or induce lay-off and pay cuts for workers. When investor enthusiasm is high, non-profitable businesses can finance cash burns through the issuance of new equity securities. Executives must take advantage of attractive loan cycles and affordable interest rates to improve the company's cash position.

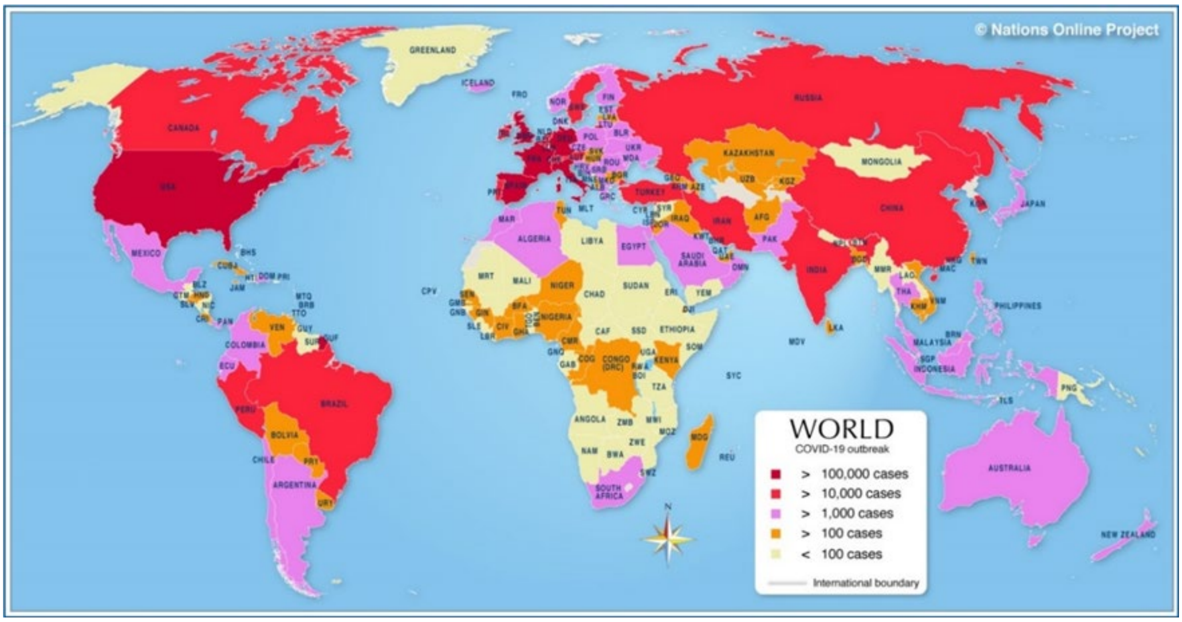
Businesses worldwide are facing an economic downturn and unprecedented challenges for survival due to COVID 19. For firms in such challenging times, foreseeing any possible issues for survival is not easy. However, to prepare for future hassle is the need of the hour. A prolonged crisis in the market is very likely to impact the liquidity of firms and during such times, the banks may lead as lenders of first resort (Li et al., 2020; Acharya and Steffen, 2020). Ever since the pandemic has started, finance research has begun to examine the economic impact of COVID-19 (Ramelli and Wagner, 2020; Zhang et al., 2020; Goodell 2020; Baker et al., 2020).

Emerging economies are characterized by a higher level of information asymmetry and a higher level of conflict of interest, between promoter managers and shareholders, due to agency problems (Manos et al., 2007; Kota and Tomar, 2010). This results in the exorbitant cost of external finance in emerging economies when financial resources are not available (Myers, 1977; Myers and Majluf, 1984). So, corporate cash holdings become of utmost importance in emerging markets and bolster the corporate position during difficult external environmental calamities. The emergence of COVID-19 is such an external environmental calamity. The current literature is curiously silent on the role of corporate cash holding as a savior during the external shock. This study is motivated to continue the trail of the economic significance of the external shock. The study finds suitable solutions for the liquidity crunch created by the drop in sales due to COVID-19. Thus, the objectives of the study are to find the impact of COVID-19 on the cash flows of the firm and to identify, determine and report the saviors of the businesses in the stressed external financing environment.

The study finds the answers to the questions such as: What happens to corporate cash holdings during an external shock in the market? How do corporate cash holdings help stressed firms? For how long do the available corporate cash holdings last? What is the role of the financial system, when the availability of credit in the financial system dries considerably? Does the borrowing pattern of firms change after the external shock? Can relying on a greater number of debt sources (Debt heterogeneity) help the firms?

The study is unique and has become prominent during the difficult times of COVID-19. Various reasons hold importance for such a study. COVID-19 has caused exceptional and unprecedented economic consequences all over the world. One such consequence experienced by the firms is the loss of sales and the resulting cash crunch. Examination of such impact will add to the research on the various impacts of COVID-19 on firms' financing. Further, external situations such as COVID-19 impact different firms differently. Thus, in this study, we examine the impact of three levels of reduced sales scenarios on the firm's cash positions. Our second objective is to examine the role of existing corporate cash holdings on illiquidity. The examination entails economic significance for firms as it will help firms to avoid illiquidity and keep the businesses afloat. Finally, the role of different sources of debt available to the firms in avoiding illiquidity should be explored.

Figure 1: The updated world map of the SARS-CoV-2 coronavirus outbreak shows countries with several confirmed COVID-19 cases (as of 17 April 2020).



For this study, we have used data for 2127 Indian-listed firms. sensitivity analysis on different scenarios of decrease in sales of 25%, 50%, and 75%, is done. The impact of the decrease in sales on operating cash flows and resultant illiquidity is examined in detail. The study establishes the role of corporate cash holdings as the savior of the business against the external calamity of COVID-19. We measure the impact on cash flows with the help of Cash burn rate (CBR). Cash burn rate measures how quickly the firm spends the money. As we start bringing the risky scenarios, we observe the decreasing CBR. As expected, the CBR ratio further shrinks as we intensify the stress rate by applying partial operating flexibility instead of full operating flexibility. Both the ratios: operating cash flow to current liabilities (CFCL) ratio and operating cash flow to total debt (CFTD) ratio show a consistent decrease with an increase in the induced stress on the sales. To prevent the cash crunch, the businesses either burn the existing corporate cash holdings or the businesses would have to increase their current and total liabilities.

Logistic regression results suggest that the corporate cash holdings act as a savior and it accounts for the decrease in the probability of the businesses getting illiquid. The likelihood of firms being illiquid significantly decreases with higher cash holdings in the firm. Leverage, gross margin, ROA, and size also have a similar effect on a decrease in the probability of firms becoming illiquid. For further clarifications on the role of leverage as a savior of businesses, the final section reports the change in debt sources used by firms after the start of the COVID-19 pandemic. Overall, the study has implications for companies, managers, and policymakers as well.

2. Empirical Design and Variable Description

The primary objective of our study is to investigate the operating cash-flow and liquidity conditions of the Indian firms due to the outbreak of the COVID-19 pandemic. This section of the paper outlines the applied methodology along with the rationale of the procedures used to empirically examine our objective. The empirical design is a multi-step approach and is divided into three broad sections. Section 2.1 outlines the framework of the study along with rationale which further enables us to estimate the changes in the cash flow due to reduction in the sales, section 2.2 describes the variable construction for the three liquidity ratios used to access the cash-flow position of the firm, and finally, section 2.3 elaborates methodology to investigate the impact of Covid-19 on the operating cash-flow and liquidity position of the Indian firms.

2.1 Framework and Rationale Building

In the first step, we describe theoretically the sensitivity of cash-flow of a firm towards the contraction in the sales or demand. The idea is to test how operating cash flow changes with changes in sales. We estimate the changes in the cash flow empirically as mentioned below (*refer,* Vito and Gomez, 2020) to estimate the changes in the cash flow empirically and the same is mentioned below.

$$\partial CFO = \frac{\partial Sales}{Sales} \times \left(\left(Sales - Op.Costs \times E_{Op.Costs}\right) \times (1 - TR) - \Delta CA \times E_{\Delta CA} + \Delta CL \times E_{\Delta CL}\right) \qquad (1)$$

Where, ∂CFO is the change in the operating cash-flow, $\frac{\partial Sales}{Sales}$ is the percentage change in the sales of the firm, $Op.Costs$ is the operating cost, TR denotes the corporate tax rate for India, ΔCA and ΔCL measure the annual change in the current asset and current liability of a firm respectively, $E_{Op.\ costs}$, $E_{\Delta CL}$, $E_{\Delta CA}$ are elasticities of operating costs, change in current liabilities, and change in current assets as compared to change in sales respectively. in other words, similar to any elasticity measure, these terms estimate the percentage change in the different variables (i.e., operating cost, change in current liability, and change in current asset) due to unit percentage change in the sales for the firm. The elasticity measures are important factors in the model, as they reflect the firm's operating flexibility to combat the adverse external shock impacting the sales of the firm. In the absence of the elasticity terms in the model, a condition where a firm's operating cost, current liability, and current asset are independent of its sales, the demand reduction in the market would impact the change in operating cash-flow even more adversely. In that case, ∂CFO would be estimated by multiplying $\partial Sales$ with (1-TR) [1]. However, in a practical scenario, reduction in sales decreases the operating cost and the working capital which in turn helps offset the adverse impact of the reduction in cash flow partially. Further, we estimate the change in current liability due to the reduction in the sales in similar lines with equation (1) (*refer,* Vito and Gomez, 2020).

$$\partial CL = \frac{\partial Sales}{Sales} \times CL \times E_{CL} \qquad (2)$$

Where ∂CL is the change in the current liability and E_{CL} is the elasticity of current liability which

[1] If we replace $E_{Op.\ costs}$, $E_{\Delta CL}$, $E_{\Delta CA}$ with zero in equation 1, then ∂CFO can be represented as:

$$\partial CFO = \partial Sales \times (1 - TR)$$

measures the percentage change in current liability with one percentage change in sales. Both the measures of ∂CFO and ∂CL will be used to calculate the financial ratios to access the liquidity condition of the firm under the adverse impact of COVID-19. These four elasticities used in Equations 1 and 2 are estimated using the below-mentioned regression model.

$$\ln(y_{ijt}) = \alpha_y + \beta_y \ln sales_{ijt} + \mu_j + \mu_t + \varepsilon_{ijt} \quad (3)$$

Where, y_{ijt} alternatively takes, operating costs, change in current assets, change in current liabilities, and current liabilities for the i^{th} firm in the j^{th} industry and year t. β_y thus represents the elasticities of operating costs ($E_{Op.\ costs}$), change in current assets ($E_{\Delta CA}$), change in current liabilities ($E_{\Delta CL}$), and current liabilities (E_{CL}). μ_j and μ_t are the industry fixed effect and the year fixed effect respectively. Once the elasticities are estimated using equation 3, they will be pushed back to the equation 1 and 2 to calculate the values of ∂CFO and ∂CL.

2.2 Variable Construction

With the theoretical understanding of the impact of contacting sales on both operating cash-flow and current liability, in the second step we first, put forward three financial ratios and emphasis their usage to determine the liquidity position of the firm. Next, we link ∂CFO and ∂CL to these financial ratios to understand the impact of the reduction in sales on these financial ratios. The three ratios measuring the liquidity conditions of the firm are: 1) cash burn out ratio, 2) operating cash-flow to current liability ratio, and 3) operating cash-flow to total debt ratio. The cash burn-out ratio (CS /CFO)[2] measures the period for which a firm can fund its operating cost instead of relying on further cash inflow from creditors or shareholders. The second ratio, Operating cash-flow to current liability (CFCL) reflects the short-term liquidity position of the firm and measures the firm's operating cash-flow position as compared with its current liability (CL). Similarly, the third ratio, operating cash-flow to total liabilities (CFTD) estimates the percentage of operating cash-flow with respect to the total liabilities (TD), describing the extent up to which a firm can pay off all its debts depending upon its operating cash flow. With the operational understanding of the ratios used in the study, we adjust these ratios to ∂CFO and ∂CL which will enable us to interpret the impact of the reduction in sales due to the impact of COVID-19. The mathematical expressions of the adjusted ratios are mentioned below.

$$Cash\ Brun\ Out\ Ratio = CBR = \frac{CS}{CFO + \partial CFO} \quad (4)$$

$$Operating\ Cash\ flow\ to\ Current\ Liability\ Ratio = CFCL = \frac{CFO + \partial CFO}{CL + \partial CL} \quad (5)$$

$$Operating\ Cash\ flow\ to\ Total\ Debt = CFTD = \frac{CFO + \partial CFO}{TD} \quad (6)$$

2 CS is the cash position of a firm. It is the combinations of the cash holding and account receivables of the firm.

Where CS is the cash position which is calculated as the sum of cash holdings and account receivable, TD is the total debt which is the summation of short-term and long-term debt, CL is the current liability, CFO is the operating cash flow. ∂CFO and ∂CL are as explained in Equations 1 and 2.

2.3 Methodology

In this section, we describe the empirical methodology specifically used for our study. To determine the impact of the reduction in sales on the cash-flow and liquidity position in the Indian firms, we apply a stress test on the liquidity ratios. We examine the sensitivity analysis into four scenarios (one base case and three simulated conditions): base or best-case scenario (i.e., no change in sales), low-risk scenario (sales decrease by 25%) moderate-risk scenario (sales decrease by 50%); and high-risk scenario (sales decrease by 75%).

We first estimate the cash flow from operations (CFO) for the year 2019 (to capture the impact of the COVID-19 outbreak). Next, we estimate sales sensitivity on cash flows (∂CFO), i.e., if sales decrease by 25%, 50%, and 75%, what impact it has on operating cash flows. To calculate the elasticities used in the calculation of ∂CFO we perform the panel data regression following equation 3 considering 5 years from March 2014 to March 2019. Post calculation of $\partial CFO\ and\ \partial CL$ we estimate the three liquidity ratios (CBR, CFCL, and CFTD) following equations 4 to 6 for all four scenarios: base case scenario, low-risk scenario, moderate risk scenario, and high-risk scenario. This will help us gather the liquidity status of firms for the short and long term.

Further, we apply stress tests on the scenarios and take into consideration the partial operating flexibility of the firm rather than full operating flexibility. Full operational flexibility is available to a firm when it can act quickly to protect the firm from the adverse impact of external shock i.e., the outbreak of COVID-19 by reducing its productivity. On the other hand, the firms which cannot adjust their operations quickly in the hour of need and face friction are assumed to be operating in partial flexibility. To examine the partial operating flexibility, the elasticities of operating costs, change in current assets, change in current liabilities, and liabilities are made half ($\frac{1}{2}El_{Op.\ costs}, \frac{1}{2}E_{CL},\ \frac{1}{2}El_{\Delta CL}, \&\ \frac{1}{2}El_{\Delta CA}$) and put into equations 1 and 2 to estimate the change in operating cash flow and current liabilities and further the three liquidity ratios following Schivardi and Gudio (2020) and Vito and Gomez (2020).

As a part of our empirical analysis, we undertake a logistic regression analysis to identify the probability of a firm being illiquid (categories using CBR ratio). We indicate firms being illiquid if the cash burn ratio (CBR) of the firm is less than zero under high risk and partial operating flexibility scenario. We perform the analysis (result reported in Table 6) by regressing an indicator variable, taking a value of 1 when the firm is illiquid and 0 otherwise on firm characteristics such as cash holdings, gross margin, leverage, size, and return on asset (ROA). The model for the regression is as follows.

$$Logit(p) = \alpha_i + \beta_1 cash\ holding_i + \beta_2 leverage_i + \beta_3 Gross\ margin_i + \beta_4 size_i + \beta_5 ROA_i + \varepsilon_i \quad (7)$$

Where, $logit(p) = \ln \frac{p}{1-p}$

Further, we investigate the impact of cash crunch or illiquidity on the debt structure of the firms. The pre and post COVID-19 era difference in the debt structure and sources of the non-financial Indian firms reveal the probable solutions to combat the cash crunch or adverse impact of reduced demand owing to a decrease in the operating cash flow of the firm. We summarise the operational definition of all the variables used in the study and present it in table 1 below.

Table 1: Operational definition of the variables used in the study

Variable	Measure/Definition
CFO	CFO=Funds from operations - Change in current assets + Change in current liabilities Funds from operations=Sales – Operating costs – Depreciation – Interest expense - Current taxes + Depreciation + Deferred Taxes
Cash Burn Rate (CBR)	Cash and cash equivalents relative to cash flow from operations
Cashflow to Current Liability Ratio (CFCL)	Cash flow from operations relative to current liabilities
Cashflow to Total Debt Ratio (CFTD)	Cash flow from operations relative to total debt
Leverage	Total borrowings relative to total assets
Cash holding	Cash and cash equivalents scaled by total assets
Gross margin	(Sales-Cost of goods sold)/sales
Size	ln(total assets)
ROA	EBIT scaled by total assets

Note: The table reports the operational definition of the variables used in the study

3. Data

To examine the impact of the COVID-19 outbreak on operating cash-flow positions of the Indian firms, we use firm-level data for Indian listed firms from the CMIE Prowess IQ data source. We begin by selecting all listed firms as of March 2019. The total number of firms is 3945. We further remove the firms having missing values of data of our concern, so that we have data of all the key variables for all the firms. This leaves us with 2127 firms. We begin by applying sensitivity analysis on different scenarios of changes in sales. We first estimate the cash flow from operations (CFO) for the year 2019. Next, we estimate sales sensitivity on cash flows, i.e., if sales decrease by 25%, 50%, and 75%, what impact it has on operating cash flows. The elasticity measures ($El_{Op.\ costs}, E_{CL},\ El_{\Delta CL}, \&\ El_{\Delta CA}$) are estimated following equation 3 from the panel data regression model for 2014 to 2019 i.e., considering 5 years of financial data of the selected firm. The firm characteristics (cash holdings, gross margin, leverage, size, and return on asset) of the firms are also calculated for the selected firms and the descriptive statistics for the variables are summarised in Table 2.

Descriptive statistics of the key characteristic variables reveal that on average the sample firms have 3.7% of cash holdings to their total asset with a standard deviation of 7%. The mean (median) value of leverage is 33.4% (24.9%) for the sample firm. The higher level of leverage as compared to the cash holdings suggests greater use of leverage than internal capital for financing the investment projects. This also indicates the deviation from the celebrated pecking order theory (Myers and Majluf, 1984), as firms are relying more on debt capital rather than internal funds. The mean (median) gross margin and ROA of our sample are 15.1% (9.8%) and 6.2% (6.9%) respectively. The average size of the sample is 7.9, while the mean operating cash flow to their total asset is 6.5% with a standard deviation of 15.5%. The descriptive statistics of gross margin, ROA, and size reflect the average key characteristics of Indian-listed firms. We observe that the value of ROA (0.062) is almost equivalent to the value of CFO (0.065). This indicates that the return on assets is determined by cash flows from operations. Cash flows from financing and investment activities do not contribute to the return on assets for the selected sample of firms.

Table 2: Descriptive statistics of characteristics variables of the firms

Variables	N	Mean	Std. Dev.	P25	Median	P75
Cash holdings	2127	0.037	0.070	0.003	0.012	0.039
leverage	2127	0.334	0.385	0.117	0.249	0.415
Gross margin	2127	0.151	0.390	0.098	0.183	0.290
ROA	2127	0.062	0.109	0.025	0.069	0.113
Size	2127	7.936	2.022	6.433	7.737	9.359
CFO(Computed)	2127	0.065	0.155	0.007	0.072	0.134

Note: The table represents the summary statistics i.e., number of the firms (N), mean (Mean), standard deviation (Std.Dev.), first quartile (P25), median (Median), and third quartile (P75) of the firm characteristics used in the study for the period of March 2014 to March 2019. *Cash holdings* are cash and cash equivalents scaled by total assets. *Leverage* is the total borrowings related to cash holdings. *Gross margin* is (Sales-Cost of goods sold)/sales. *ROA* is earnings before interest and taxes scaled by total assets. *Size* is calculated as the natural log of total assets, and CFO is the computed cash flow from operations.

In Table 2, we display the summary statistics for the returns on the industry portfolios as well as our new COVID-19 attention variable. During our sample period, the durables sector witnesses the highest daily average return, approximately 30%, while energy exhibits the worst, with an average of –23%. Durables and energy are also the most volatile sectors. Shops, consisting of wholesale and retail, along with healthcare, have the lowest standard deviations among all industries. The descriptive statistics for the COVID-19 attention variable are provided in the last row. The COVID-19 attention has a mean of 3.59% and standard deviation of 23.95%.

Table 2: Descriptive Statistics – Industry Returns

	Mean	Median	St. dev.
NoDur	-0.0036	0.0900	2.4217
Durbl	0.3022	0.3500	3.7583
Manuf	-0.0286	0.0100	3.2534
Enrgy	-0.2331	-0.3000	4.3949
Chems	0.0410	0.1300	2.5460
BusEq	0.1783	0.4800	2.8779
Telcm	-0.0156	0.1600	2.4197
Utils	-0.0159	0.1300	3.0605
Shops	0.1623	0.2500	2.2705
Hlth	0.0656	0.0700	2.2893
Money	-0.0702	-0.0100	3.5400
Other	-0.0103	0.2200	2.8526
COVID-19 attention	0.0359	0.0000	0.2395

Note: This table presents mean, median, and standard deviation of returns for each industry listed in the first column. The COVID-19 attention variable is provided in the last row. The sample period is 1 January – 31 July 2020.

4. Result

The result section of our study is divided into three sections. The first sub-section reports the result of the stress test or sensitivity analysis of the three ratios simulated for reduced demand scenarios (low-risk, moderate-risk, and high-risk conditions with full and partial operating flexibility). The result of the logistic regression analysis for illiquid firms is reported in the second sub-section. Finally, The third sub-section reports the debt heterogeneity in terms of the debt sources among the Indian firms before and after the COVID-19 outbreak.

4.1 Stress Tests on Financial Ratio

Table 3 presents the results of the stress test of three ratios for the best-case scenario i.e., with no change in the sales (panel A) along with three simulated scenarios (panel B to G). According to panel B of Table 3, in the best-case scenario, the cash burn out ratio measures how quickly the firm spends the money shows that with no change in sales for an average firm in our sample, the cash holdings account for about two months for a firm (mean CBR in panel A). Moving forward to the stimulated scenarios, we find that the cash holding period reduces from about one and a half months (mean CBR of panel B) to less than a month (mean CBR of panel D) for low-risk scenario to high-risk scenario, respectively in case of full operating flexibility. On the other hand, in the case of partial operating flexibility, CBR becomes negative for all the three risk scenarios revealing that firms will not be able to hold any cash reserves with the reduced sales (mean CBR in panels E, F, and G). The poor cash holdings position with respect to the annual operating cash-flow of an average firm reveals the existing cash crunch in the firms.

Table 3: Stress test result for CBR, CFCL, and CFTD for low-risk, moderate-risk, and high-risk scenarios with full and partial operating flexibility

Panel A: Base case scenario (No change in sales)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	0.16	0.041
CFCL	2127	0.507	0.498
CFTD	2127	6.34	0.641
Illiquid firms	534		
Full operating flexibility			
Panel B: Low risk scenario (Sales drop by 25%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	0.134	0.037
CFCL	2127	0.364	0.319
CFTD	2127	5.794	0.584
Illiquid firms	426		
Panel C: Moderate risk scenario (Sales drop by 50%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	0.101	0.031
CFCL	2127	0.319	0.289
CFTD	2127	4.57	0.488
Illiquid firms	446		

Panel D: High-risk scenario (Sales drop by 75%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	0.078	0.027
CFCL	2127	0.269	0.249
CFTD	2127	3.389	0.378
Illiquid firms	476		
Partial operating flexibility			
Panel E: Low risk scenario (Sales drop by 25%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	- 0.15	- 0.033
CFCL	2127	- 1.198	- 1.005
CFTD	2127	- 13.963	- 1.483
Illiquid firms	213		
Panel F: Moderate risk scenario (Sales drop by 50%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	- 0.087	- 0.025
CFCL	2127	- 0.857	- 0.726
CFTD	2127	- 10.173	- 1.066
Illiquid firms	236		
Panel G: High-risk scenario (Sales drop by 75%)			
Ratio	**N**	**Mean**	**Median**
CBR	2127	- 0.061	- 0.019
CFCL	2127	- 0.551	- 0.479
CFTD	2127	- 6.307	- 0.678
Illiquid firms	301		

Note: The tables report the mean and median of CBR (cash burn ratio), CFCL (cash-flow to current liability ratio), and CFTD (cash-flow to total debt ratio) calculated for seven scenarios (Panel A to G). Panel A reports the ratios for the base case with no change in the sales. Panel B to D report the ratios when reduced sales for 20%, 50%, and 75% and considering fully operational flexibility. Similarly, Panels E to G reports the ratios when reduced sales for 20%, 50%, and 75% and considering fully operational flexibility. The row termed illiquid firms in each panel report the number of firms whose CBR is less than 0.

Next, we analyze the liquidity situation of a firm in terms of the average operating cash flow to current liabilities (CFCL) ratio. In the base case, on an average firms would be able to cover about 51% (mean CFCL of panel A) of their current liability through the operating cash-flow generated from sales. When the sales are reduced by 25% and firms are assumed to have full flexibility, their capability of covering the current liability through the operating cash flow will be reduced to 36% (mean CFCL of panel B). However, in the high-risk scenario, firms' capacity of covering their current liability will be about 27% (mean CFCL of panel D). The CFCL ratios in the case of partial operating flexibility can be interpreted in the same way. Similar to CBR, CFCL becomes more problematic when the firms are assumed to run in partial operating flexibility. The CFCL ratios for all three risk scenarios (low, medium, and high) are negative, averaging from about -119% to -55% (mean CFCL in panel E, F, and G) showing that firms will be incapable to pay off their current liability using the cash flow generated from cash flow under the reduced demand i.e., a spillover effect.

The evidence of spillover from the CFCL ratio is also supported by the stress test result of CFTD. CFTD measures the percentage of operating cash flow corresponding to the total debt of a firm. When the firms are assumed to be operating with partial flexibility the ratio becomes negative for all three risk scenarios (mean CFTD in panels E, F, and G) indicating that the firms would need to borrow more to be able to operate in the reduced demand situations.

Apart from the three financial ratios, we also report the number of illiquid firms calculated for each scenario separately. The number of illiquid firms is calculated based on the value of the CBR. The firms are termed to be illiquid when the CBR value is less than zero and becomes negative. The number of illiquid firms ranges from 213 to 534 among different scenarios. Overall, the result of stress tests simulated for three risk conditions suggests that to avoid the cash crunch during an external shock to the firms, they need to borrow more to sustain themselves in the market.

4.2 Characteristics of the Illiquid firms

Further, we investigate the illiquid firms identified for the extreme case i.e., high-risk scenario operating with partial flexibility in terms of their characteristics such as cash holdings, leverage, gross margin, size, and ROA. The illiquid firms are those whose CBR is less than 0 for the extreme condition (total 301 firms). We perform two types of analysis: 1) univariate analysis where we report the differences between the key characteristics of the firms divided into categories of liquid and illiquid firms in terms of CBR of extreme condition, and 2) logistic regression where the dependent variable is an indicator of whether a firm is illiquid or liquid and the independent variables are the firm characteristics as mentioned earlier (equation 7). Table 4 reports the result of the univariate analysis. It shows that out of 2127 firms in our sample 301 firms are categorized as illiquid in the extreme scenario i.e., at high-risk where the demand is reduced by 75% and firms are operating in partial flexibility.

Table 4: Differences between liquid and illiquid firms with partial operating flexibility in the high-risk scenario

Variable	Liquid firms	Illiquid firms	Difference	T-stat
Cash holding	0.039	0.022	0.017	4.068
Leverage	0.332	0.35	-0.018	-0.77
Gross Margin	0.146	-0.978	1.124	4.692
Size	7.986	7.632	0.354	2.816
ROA	0.066	0.038	0.028	4.193
Obs.	1826	301		

Note: The table presents the differences between liquid and illiquid firms. Column 1 presents the mean values of variables for liquid firms, and column 2 presents the mean values for illiquid firms. Columns 3 and 4 report the difference in the variables and the T-statistics of mean differences between liquid and illiquid firms respectively.

From the difference and the associated T-stat of the key characteristics of the two categories of the firm, it can be commented that the illiquid firms are smaller in size, possess fewer cash holdings, and earn less gross margin and ROA. The leverage level of illiquid firms is higher although the t-stat is not significant for the same. Next, Table 5 reports the result of the logistic regression analysis which reveals the probability of a firm being illiquid depending upon its key characteristics. The result of the logistic regression is the validation of the univariate analysis. We perform two regression models with and without including the industry fixed effect to control for the industry shock which could modify the probability of a firm being illiquid. The first and third columns report the regression coefficients of logit regression without and with industry fixed effects respectively.

The second and fourth columns report the marginal effects of each variable. The results suggest that cash holding accounts for the decrease in the probability of the firms getting illiquid. The likelihood of firms being illiquid significantly decreases with higher cash holdings in the firm. Gross margin, ROA, and size also account for the decrease in the probability of firms becoming illiquid. In terms of economic significance, one standard deviation increase in the cash holdings of a firm leads to a 4.07% (marginal effect * standard deviation= 58.22* 0.07) decrease in the chance of it becoming illiquid. Similarly, one standard deviation increase in gross margin, ROA, and size of a firm leads to a 0.59%, 1.52%, and 1.66% decrease in the chances of it becoming illiquid respectively. The leverage difference between liquid and illiquid firms is not significant. The results are consistent while using the industry effect as well. The key characteristics analysis of the illiquid firm reveals that firms should pay attention to building their cash reserve, and aim to earn higher ROA to combat the cash crunch situations.

Table 5: Result of determinants of illiquidity

Variable	Illiquidity	Marginal effects	Illiquidity	Marginal effects
Cash holding	-4.983***	-58.22%	-4.745***	-55.99%
	-1.3		-1.281	
Leverage	-0.078	-0.91%	-0.097	-1.14%
	-0.1		-0.103	
Gross Margin	-0.130**	-1.52%	-0.126**	-1.49%
	-0.053		-0.054	
Size	-0.070**	-0.82%	-0.080**	-0.95%
	-0.033		-0.033	
ROA	-1.195*	-13.96%	-1.399**	-16.51%
	-0.615		-0.606	
Industry FE	YES		NO	
Constant	-1.230***		-0.926***	
	-0.286		-0.271	
Obs.	2127		2127	
Pseudo R2	0.0418		0.0307	

Note: The table presents the results of the regression for determinants of illiquidity. The dependent variable is the dum with a value of 1 for illiquid firms and 0 for liquid firms. Cash holdings are cash and cash equivalents scaled by total ass Leverage is the total borrowings related to cash holdings. Gross margin is (Sales-Cost of goods sold)/sales. ROA is earni before interest and taxes scaled by total assets. Size is calculated as the natural log of total assets, and CFO is computed cash flow from operations. Standard errors are in parenthesis with, ***, **, and, * p<0.1 denote the significa level at 1%, 5%, and 10% levels, respectively.

4.3 Debt Heterogeneity as saviour during COVID-19

After observing an insignificant impact of the leverage on the firm's liquidity position, in this section, we further investigate the impact of cash crunch or illiquidity on the debt structure of the firms. We explore the link between the two and suggest a future direction to finance research. We source the debt heterogeneity pattern data of Indian firms from the Prowess IQ database. The database provides us not only the total debt used by the firms but also describes each component in total debt [3]. Each debt source account for different characteristics and thus indicates the quality of the firm [4], thus examining the debt heterogeneity pattern becomes imperative. We source the debt structure data for pre and post COVID-19. For reference, Feb-20 is considered as the pre-COVID-19 period and April-20 is taken for the post-COVID-19 period (As it was only from March 22, 2020, the Government of India announced the nation-wide lockdown).

3 This definition of debt heterogeneity takes into account of both long term and short-term debt sources and among these sources, the actual source of borrowings is considered.

4 Refer to Rauh and Sufi, 2010 & Colla et al., 2013

Table 6: Change in debt structure patterns after COVID-19. Data sourced for 3952 non-financial listed firms as of March 2020 from the CMIE Prowess IQ database

Variables	Feb-20 In Rs. (Millions)	Apr-20 In Rs. (Millions)	(+) Increase or (-) Decrease
Bank borrowings	4041	8825	4784
Financial Institution borrowings	850	699	-151
Government borrowings	1473	1574	101
Syndicated borrowings	20533	627	-19905
Debentures and bonds	21729	36903	15174
Foreign currency borrowings	10268	8281	-1987
Loans from promoters and directors	75	71	-3
Inter-corporate loans	756	2271	1515
Deferred credit	5490	7824	2334
Interest accrued and due	851	199	-652
Hire Purchase loans	1647	2096	449
Fixed deposits	248	334	86
Commercial Paper	20264	16672	-3593
Other Borrowings	1251	6772	5521
Total borrowings	5913	1916	-3997

Note: Table reports the change in the uses of types of debt sources in the pre and post COVID-19 period.

We observe a substantial decrease in the total borrowings of the firms, however, the contribution from a few of the debt lenders increased. The maximum increase in the contribution of debt is from the debentures and bonds borrowings. Bank borrowings have increased. The increase in bank borrowings indicates bankers as the lenders of first resort. The increase in inter-corporate loans also indicates an increase in uses of the long-lived king of corporate cash holding in helping not just own businesses but for businesses of related and concerned parties.

4. Implication and conclusions of the study

The empirical investigation performed in various stages reveals both current cash-flow or liquidity conditions and future adverse impact on cash flow due to reduction in the demand for the Indian firms. Finally, we summarise the outcomes of the investigation and outline probable solutions to manage the adverse impact of COVID-19 on sales. Stress test results show that due to reduction in sales firms become illiquid and cannot repay their current liabilities using the cash flow from the operations. Further key characteristics analysis of the illiquid firms reveals that smaller firms, having less gross margin, earning lesser ROA are more suspectable to become illiquid in an adverse condition. Finally, pre and post COVID- 19 era debt structure comparison for the Indian firms indicates that diversified loan structure may help the firm overcome the cash crunch situations created due to the adverse shock of the pandemic. Apart from the use of various debt sources, the firms should have access to inexpensive short-term loans granted by the Government or other regulated market sources to mitigate the illiquidity conditions. A tax-deferral provision can also be considered as another way to solve the problem.

Retained cash holdings act as the saviour during the difficult times of extremely adverse macroeconomic conditions, one of which is presented to human society with the outbreak of the global pandemic of COVID-19. In a perfect market condition, corporate cash holding should not matter. But in this study, our objective was to check the sensitivity of operating cash flows, by considering, different scenarios of sales drop due to COVID-19. The resultant impact on operating cash flows and illiquidity and role of corporate cash holdings in decreasing the pace of cash burn rate and prolonging the life of the businesses by avoiding illiquidity in the short run or till the time adverse external macroeconomic environment stabilizes. Corporate cash holdings are helpful in avoiding the cash crunch of the businesses and acts as a saviour of business. Thus, justifies our title COVID-19 is deadly! Long Live the King, Corporate Cash Holdings!

References

Acharya, Viral, and Sascha Steffen. "Stress tests" for banks as liquidity insurers in a time of COVID." *VoxEU. org, March* 22 (2020).

Al-Dhamari, R., & Ismail, K. N. I. K. (2015). Cash holdings, political connections, and earnings quality. *International Journal of Managerial Finance*.

Al-Najjar, B. (2013). The financial determinants of corporate cash holdings: Evidence from some emerging markets. *International business review*, *22*(1), 77-88.

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *Covid-induced economic uncertainty* (No. w26983). National Bureau of Economic Research.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to?. *The journal of finance*, *64*(5), 1985-2021.

Baumol, W. J. (1952). The transactions demand for cash: An inventory theoretic approach. *The Quarterly Journal of Economics*, 545-556.

Chen, Y. R., & Chuang, W. T. (2009). Alignment or entrenchment? Corporate governance and cash holdings in growing firms. *Journal of Business Research, 62(11)*, 1200-1206.

Colla, P., Ippolito, F., & Li, K. (2013). Debt specialization. *The Journal of Finance*, *68*(5), 2117-2141.

De Vito, A., & Gomez, J. P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*, 106741.

Duchin, R. (2010). Cash holdings and corporate diversification. *The Journal of Finance*, *65*(3), 955-992.

Denis, D. J., & Sibilkov, V. (2009). Financial constraints, investment, and the value of cash holdings. *The Review of Financial Studies*, *23*(1), 247-269.

Ferreira, M. A., & Vilela, A. S. (2004). Why do firms hold cash? Evidence from EMU countries. *European financial management*, *10*(2), 295-319.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 101512.

Habib, A., & Hasan, M. M. (2017). Social capital and corporate cash holdings. *International Review of Economics & Finance*, *52*, 1-20.

Harford, J. (1999). Corporate cash reserves and acquisitions. *The Journal of Finance*, *54*(6), 1969-1997.

Kalcheva, I., & Lins, K. V. (2007). International evidence on cash holdings and expected managerial agency problems. *The review of financial studies*, *20*(4), 1087-1112.

Keynes, J. M. (1934). *The applied theory of money* (Vol. 2). Macmillan and Company.

Kota, H. B., & Tomar, S. (2010). Corporate governance practices in Indian firms. Journal of Management & Organization, 16(2), 266-279.

Li, L., Strahan, P. E., & Zhang, S. (2020). Banks as lenders of first resort: Evidence from the Covid-19 crisis. *The Review of Corporate Finance Studies*.

Manos, R., Murinde, V., & Green, C. J. (2007). Leverage and business groups: Evidence from Indian firms. Journal of Economics and Business, 59(5), 443-465.

Mulligan, C. B. (1997). Scale economies, the value of time, and the demand for money: Longitudinal evidence from firms. *Journal of Political Economy*, *105*(5), 1061-1079.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of financial economics*, *5*(2), 147-175.

Myers, S. C., & Majluf, N. S. (1984). *Corporate financing and investment decisions when firms have information that investors do not have* (No. w1396). National Bureau of Economic Research.

Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of financial economics*, *52*(1), 3-46.

Schivardi, F., & Guido, R. (2020). A simple method to estimate firms' liquidity needs during the Covid-19 crisis with an application to Italy.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

RELATION BETWEEN NEGATIVE TONE IN NEWS RELEASES OF WHO AND INDUSTRY RETURNS DURING THE COVID-19 PANDEMIC

Denada Ibrushi[1*] and Helmi Jedidi[2]

1. Greehey School of Business, St. Mary's University, San Antonio Texas
2. Deloitte Montreal, Canada

* Corresponding Author: Denada Ibrushi, Assistant Professor of Finance, Greehey School of Business, St. Mary's University, 1 Camino Santa Maria San Antonio Texas, 78228
✉ Email: dibrushi@stmarytx.edu

Abstract

We analyse the relationship between the negative tone in news releases issued by the WHO and industry returns during the COVID-19 pandemic. We construct our news tone measure as the ratio of negative words to the total number of words present in news releases of WHO. The news tone shows to be significantly associated with returns for the majority of industries. Bad news announced by the WHO translates into good news for consumer nondurables, telecommunications, and healthcare sectors. Negative tone in news releases of WHO is on average bad news for consumer durables, manufacturing, energy, and other industries. Our findings suggest that the news tone-return relation varies significantly throughout our COVID-19 sample.

Keywords: News Tone; WHO; COVID-19; Industry returns.

1. Introduction

Stock markets plunged on March 11, 2020, as the World Health Organization (WHO) declared the rapidly spreading coronavirus a global pandemic. The Dow dropped by approximately 1,500 points after the WHO's announcement. The Standard & Poor 500 closed at a 4.9% fall for the session. In a Washington Post article, Taylor and Heath (2020) report that industrials, financials, energy, and real estate were the sectors mainly affected by the pandemic announcement, while the health sector was least affected. While the pandemic announcement has been crucial in terms of its impact on financial markets across the globe, it is important to note that the WHO issued multiple news releases before as well as after the announcement of the global pandemic. Garcia (2013) underlines the importance of news arrival in resolving uncertainty during periods of economic recession by reporting that the impact of media pessimism on the Dow Jones index is three times higher in recession than in expansion. However, this last recession, because it resulted from a public health crisis, made everyone stay focused on one main organization: the WHO. A recent research report (Shearer, 2020) shows that 51% of U.S. adults consider public health organizations and officials a major source for news about the coronavirus outbreak. While the slow response of the WHO to the COVID-19 has been under criticism, Kuznetsova (2020) as well as a recent editorial of the Nature Microbiology stress the importance of the WHO in preventing and controlling global outbreaks. Both studies show that the WHO learned its lessons from coronavirus and with the right resources it will exhibit successful response to potential health threats. Consequently, in this article we seek to examine the impact of various news releases published on the WHO's website during the first seven months of 2020. More specifically, we analyze how the tone of these releases affects stock returns across twelve industry portfolios constructed by Professors Fama and French and available on Professor Kenneth French's website.

It has been widely discussed in literature the role that the tone of news plays in stock market reactions. In a recent paper, Ahmad et al. (2016) finds that during certain episodes the media tone has a temporary effect on firm returns and on others a permanent one. Tetlock (2007) asserts that tone in media includes new information about fundamental value, contributing to an important side of the literature (Groß-Klußmann and Hautsch, 2011; Loughran and McDonald, 2011; Dzielinski and Hasseltoft, 2013; Heston and Sinha, 2017) that documents a significant relationship between the negative tone in news and negative next-day returns. We contribute to a growing literature addressing the impact of news tone at different firm and market levels by measuring the negative news tone in WHO releases and studying its relation to industry returns during the COVID-19 pandemic. To the best of our knowledge, this is the first study to evaluate the negative tone (used interchangeably with news tone hereinafter) of news releases published by the WHO during the COVID-19 pandemic and relating it to sector returns.

In this paper, we first measure the tone of news releases available on the WHO's website[1] during our COVID-19 sample period. We apply Natural Language Processing (NLP) techniques for our textual analysis and use the Loughran and McDonald (2011) dictionary as our benchmark to measure the proportion of negative words to the total number of words within a news release. We manually extend the pre-set group of words in the Loughran and McDonald (2011) dictionary to account for health-related terminology. On average, we observe 36 days with news releases that were published by the WHO and carry the "Coronavirus disease (COVID-19)" tag. May is the month with the highest number of articles whereas July and March are characterized by the most negative tone in news. The news tone for the whole sample period has a mean of 6.4% and standard deviation of 2.2%. Constructing a measure of the news tone present in the WHO's news releases and studying its impact during the COVID-19 pandemic can help us understand better and resolve uncertainty during recessions of a public health nature.

Our findings show a significant relationship between the WHO's news tone and returns at the industry level. The consumer nondurables, telecommunications, and healthcare sectors react positively to increased negative news from the WHO. In contrast, consumer durables, manufacturing, energy, and other sectors are negatively related to its bad news. Financial companies remain resilient to negative news. Chemicals, shops, and business equipment industries are also not susceptible to negative news released by the WHO. It is worth noting that this article does not consider predictability patterns using lagged news tone measures. While this is an important exercise for future research as more data becomes available, at this phase it is optimal to focus on determining whether there is a significant relation in the first place. Last but not least, implementing the rolling window approach that is commonly applied in similar studies (Ahmad et al. (2016)), we observe that the impact of news tone on returns is not only significant for most of the industries but also varies throughout the COVID-19 period. In agreement with Bianchi (2020), we also believe that rare events in previous periods affect investors' expectations and therefore we anticipate the COVID-19 pandemic to have a significant impact in determining investors' expectations even after the pandemic ends. Our results suggest that the WHO should be viewed as an important news source affecting stock returns.

[1] www.who.int.

Our paper complements the evolving literature that is investigating financial markets during the COVID-19 pandemic. Goodwell (2020) is one of the pioneers of the COVID-19 literature, contributing tremendously by providing guidance on potential topics that address the impact of the pandemic. Baker et al. (2020) use text-based methods in their study of stock market reaction during coronavirus versus previous pandemics. They find that government restrictions on commercial activity as well as social distancing are the prior reasons the U.S. stock market reacted strongly to COVID-19 than to previous virus outbreaks. Ramelli and Wagner (2020) is another interesting study demonstrating that the expected effects from COVID-19 are amplified through financial channels. Erdem (2020) identifies differences in the effects of COVID-19 news on stock indices in free versus non-free regimes. While Erdem uses the term "news," it does not refer to a direct news measure in a published text as is our case with WHO publications; he defines news as incoming data about the number of cases and deaths per million. Likewise, Haroon and Rizvi (2020) study how markets behave toward media coverage. They obtain their panic, sentiment, and media coverage indices externally and document that panic in news is related to higher volatility in stock markets. In another study, Ding et al. (2020) use Google trends related to COVID-19 to model market sentiment, a variable that we also estimate and use as a control variable in our specification. This article documents that the most digitally transformed industries remain resilient to negative sentiment in the market. He et al. (2020) also examines the impact of COVID-19 on different industries and report that the Chinese sectors more negatively affected are mining, transportation, electricity and heating, and the environment. Smales (2021) is another paper close to ours based on the heterogeneous impact of its attention variable across different sectors during the COVID-19 crisis. It is important to emphasize that the attention variable of this paper is equivalent to the COVID-19 attention variable that we include in our analysis as a control variable. Our article fortifies the argument that neither the COVID-19 attention variable nor our news tone sentiment from issued news articles of the WHO are the only factors affecting stock returns during the pandemic. More importantly, we show that our news tone variable exhibits a significant impact even when we control for the COVID-19 attention variable and that it affects distinct sectors differently. Motivated by this literature, we construct our measure for tone present in the WHO's news releases and study its impact on multiple industries over the span of the COVID-19 pandemic.

The rest of the paper is organized as follows. Section 2 describes the data and the steps we take to build the news tone measure. Section 3 provides methodology and results, and Section 4 shares conclusions and suggestions for future research.

2. Building News Tone Measure and Data Description

We apply Natural Language Processing (NLP) techniques to analyze the textual content of news releases issued by the WHO. We start by scraping the WHO website to retrieve the Hypertext Markup Language (HTML) elements for all news releases tagged with "Coronavirus disease (COVID-19)" in the WHO newsroom between January 1 and July 31, 2020. After gathering the text body of each news release, we continue with the following steps: i) tokenization, ii) expanding contractions, iii) removing stop words, iv) stemming and lemmatization, v) part-of-speech (POS) tagging, and vi) word classification. Tokenization consists of breaking down each news article into single words called tokens. We then expand the shortened versions of spoken forms of words so that they can be easily matched in the following steps. In the next step, punctuation, special characters, non-numerical characters as well as stop words are removed from the news article. This ensures mitigation of extra noise from unstructured texts. Stemming and lemmatization consist of reducing derivationally related words into their common root (lemma). Afterwards, we identify the grammatical grouping of tokens via POS tagging. Finally, we conduct sentiment (tone) analysis using text classification. The Loughran and McDonald (2011) financial sentiment dictionary serves as our benchmark to capture tone in WHO's news releases. Furthermore, we extend the Loughran and McDonald (2011) dictionary and its terminology by accounting also for pandemic context and health-related terms. We finally construct our news tone measure as the percentage of negative words to the total number of words present in a news article/s issued by the WHO within a day.

We obtain our daily Fama-French factors and industry return data from Professor Kenneth French's website. The market, size, and value factors are used as control variables in our regression analysis in Section 3. We also control for the change in "coronavirus" Google trends and denote this measure as the COVID-19 attention variable. The trend of search volume for the word "coronavirus" is based on global searches from Google trends analytics. The twelve industries included in this study are as follows: consumer nondurables (NoDur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), chemicals (Chems), business equipment (BusEq), telecommunications (Telcm), utilities (Utils), shops (Shops), healthcare (Hlth), financials (Money), and others (Other). Industry portfolios are built based on NYSE, AMEX, and NASDAQ stocks.

Table 1 presents the summary statistics of our negative news tone variable as well as the number of news articles issued on a monthly basis. Considering the constrained number of observations for the month of January, we report the descriptive statistics of January and February jointly. The second column reports the number of issued news articles. Ten news articles were issued in May, rendering it the month with the highest number of articles. April is the second month with 7 articles. Focusing on the statistics of news tone, we find that the proportion of negative words in the news articles of the WHO is highest in July and March. The lowest extent of negative tone in issued articles is observed in April. The median and standard deviation estimates are reported in the last two columns. The last row of Table 1 indicates that in total we have 36 news articles with an average negative tone of 6.40% and standard deviation of 2.22%.

Table 1: Descriptive Statistics – News Articles and Negative Tone

	News Articles	Mean	Median	St. dev.
Jan and Feb	5	0.0679	0.0619	0.0196
March	5	0.0694	0.0677	0.0211
April	7	0.0513	0.0482	0.0138
May	10	0.0664	0.0680	0.0182
June	5	0.0620	0.0590	0.0371
July	4	0.0714	0.0590	0.0301
Overall Sample	36	0.0640	0.0614	0.0222

Note: This table presents the number of news articles, mean, median, and standard deviation of negative tone for each month listed in the first column. Estimates for January and February are reported together due to the limited number of observations in January. The summary statistics for the overall sample are presented in the last row. The sample period is 1 January – 31 July 2020.

In Table 2, we display the summary statistics for the returns on the industry portfolios as well as our new COVID-19 attention variable. During our sample period, the durables sector witnesses the highest daily average return, approximately 30%, while energy exhibits the worst, with an average of –23%. Durables and energy are also the most volatile sectors. Shops, consisting of wholesale and retail, along with healthcare, have the lowest standard deviations among all industries. The descriptive statistics for the COVID-19 attention variable are provided in the last row. The COVID-19 attention has a mean of 3.59% and standard deviation of 23.95%.

Table 2: Descriptive Statistics – Industry Returns

	Mean	Median	St. dev.
NoDur	-0.0036	0.0900	2.4217
Durbl	0.3022	0.3500	3.7583
Manuf	-0.0286	0.0100	3.2534
Enrgy	-0.2331	-0.3000	4.3949
Chems	0.0410	0.1300	2.5460
BusEq	0.1783	0.4800	2.8779
Telcm	-0.0156	0.1600	2.4197
Utils	-0.0159	0.1300	3.0605
Shops	0.1623	0.2500	2.2705
Hlth	0.0656	0.0700	2.2893
Money	-0.0702	-0.0100	3.5400
Other	-0.0103	0.2200	2.8526
COVID-19 attention	0.0359	0.0000	0.2395

Note: This table presents mean, median, and standard deviation of returns for each industry listed in the first column. The COVID-19 attention variable is provided in the last row. The sample period is 1 January – 31 July 2020.

3. Methodology and Results

In this section, we explain the methodological framework and examine the relationship between our variable of interest, the negative news tone in WHO releases, and industry returns. In the same spirit as Ahmad et al. (2016), who use rolling vector autoregressive regressions to determine the impact of news tone at firm level at different points in time, we utilize rolling windows of 60-day observations to estimate the effect of news tone on sector returns. Considering the limited data availability, we choose 60 days to be our optimal window size that also includes a sufficient number of news releases.[2] We thus have an average of 15.4 news releases per rolling window. Our regression sample starts with the first news release available, published on January 21.

For a rigorous analysis of the relationship between news tone and sector returns, we run a slightly revised version of Fama and French, including an additional control variable next to the systematic factors of market, size, and value. We thus include the market sentiment proxy captured by the change in our COVID-19 attention measure. We also look at other measures, such as change in the number of new cases and deaths and observe that they are highly correlated not only to each other but also to our attention variable. Moreover, our results in Table A1 from the appendix section show that the main patterns indicating the impact of news tone continue to hold in the presence of a control variable for the new cases of COVID-19. Considering the sample size, we do not include these two variables in our main specification. Unlike studies (Tetlock (2007) and Ferguson et al. (2015)) that exclude all dates with no news releases, we follow Ahmad et al. (2016) and set to zero the dates when no news

[2] Our results remain qualitatively the same when trying rolling windows of 40 and 50 days.

was announced by the WHO. These zero news dates lead to downward-biased coefficients in absolute value and lower probability of significant results. Having determined the optimal window size and the independent variables, we now estimate the following regression:

$$R_{j,t} = \alpha_j + \beta_{MKT,j}MKT_t + \beta_{SMB,j}SMB_t + \beta_{HML,j}HML_t + \beta_{Att,j}Att_t + \beta_{Tone,j}Tone_t + \varepsilon_t \quad (1)$$

where $R_{j,t}$ denotes returns in excess of the risk-free rate for industry j on day t. MKT, SMB, and HML denote excess market return, size, and value Fama-French factors. Att is the change in COVID-19 attention variable, and $Tone$ is our measure of negative news tone.

Table 3: Impact of News Tone on Different Industries

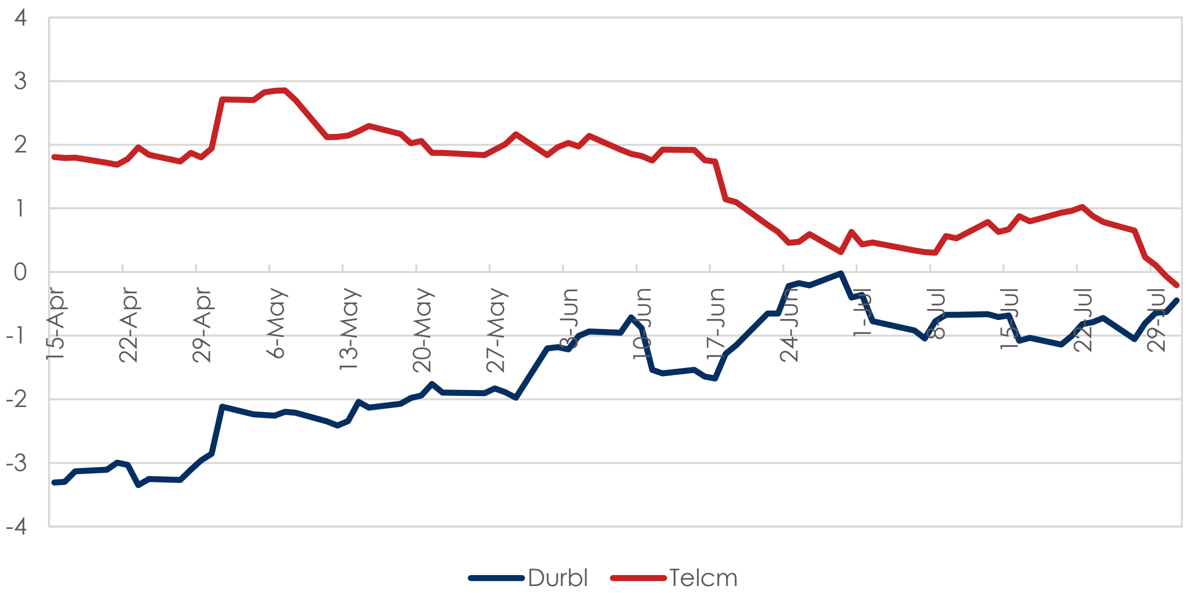
	β_{MKT}	β_{SMB}	β_{HML}	β_{Att}	β_{Tone}
NoDur	0.7921 ***	-0.0820 ***	0.1200 ***	0.4844 ***	3.1356 ***
Durbl	1.1246 ***	0.4083 ***	0.0940 ***	-1.7601 ***	-15.2432 ***
Manuf	1.0403 ***	0.0885 ***	0.4352 ***	1.0813 ***	-1.3179 ***
Enrgy	1.1702 ***	0.2738 ***	0.8041 ***	0.7207 ***	-10.6476 ***
Chems	0.8621 ***	-0.2170 ***	0.1596 ***	1.8222 ***	-0.2439
BusEq	1.1161 ***	0.0057	-0.3457 ***	-0.5854 ***	-0.1171
Telcm	0.8076 ***	-0.0516 ***	0.1819 ***	0.6213 ***	5.4529 ***
Utils	0.9783 ***	-0.2799 ***	0.2034 ***	0.8898 ***	-0.8850 ***
Shops	0.8611 ***	0.0366 **	-0.2854 ***	-0.5902 ***	-0.1855
Hlth	0.8965 ***	-0.0653 ***	-0.2484 ***	1.0423 ***	2.2015 ***
Money	1.0991 ***	-0.1040 ***	0.6255 ***	0.0533	0.0114
Other	0.9232 ***	0.2040 ***	0.2801 ***	0.0154	-2.3268 ***

Note: This table presents the average factor loadings in Equation (1) for each industry listed in the first column. The coefficient estimates are obtained from 60-day rolling windows of observations during our sample period of 21 January 2020 – 31 July 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 presents results from Equation (1) to analyze the relationship between industry returns and news tone. On average, we find a significantly positive association between the WHO's news tone and returns for consumer nondurables, telecommunications, and healthcare sectors. A one-percent change in news tone is associated with approximately 5% higher returns for telecommunications, rendering it the most positively sensitive sector to the negative toning of news. The finance sector is also positively related to news tone but not at a significant level. In contrast, there is a negative relationship between news tone and returns for consumer durables, manufacturing, and energy. Consumer durables dominates, with a negative change of 15% in stock returns per percentage change in news tone. Utilities is also negatively affected but to a lower extent (-0.89%). As expected, we observe a significantly negative impact of more negative news on the last "Other" category, which includes mines, construction, building materials, transportation, hotels, bus services, and entertainment. In unreported results, we also consider the 30 industries classified by Fama and French and it is evident that the main sectors driving the results for the "Other" category are those of hotels and transportation. The lack of significance for chemicals, business equipment, shops, and financials is an interesting finding indicating that those sectors are resilient to the toning of news by the WHO. Focusing on the economic importance of our results, we find that one standard deviation change in the news tone is associated with respective changes of 0.0696%, 0.1211%, and 0.0489% for the non-durables, telecommunications, and healthcare, which are the sectors that demonstrate a positive significant relationship. On the other side, one standard deviation change in news tone is related to 0.3384% and 0.2364% change for durables and energy sectors. Varying between 0.0196% and 0.0517%, the impact is much lower for manufacturing, utilities, and other sectors. It is important to emphasize that we do not claim to build a new systematic factor in addition to Fama-French factors. Our goal is to understand the value of tone in news issued by the WHO during biological recessions and how it relates to different sectors over the pandemic, while also controlling for market, size, value and COVID-19 attention factors.

Documenting that consumer durables and telecommunications are the two main sectors representing opposite relations between news tone and industry returns, we now focus on the time variation of this news tone–return relation for these two sectors during our COVID-19 sample. In Figure 1, we plot the t-statistics for consumer durables and telecommunications based on 60-day rolling windows with ending dates as shown on the horizontal axis. We observe varying magnitudes and significance levels for our coefficient estimates. Put differently, the impact of news tone not only differs across industries, but also exhibits variation across time. It is evident from Figure 1 that news tone and returns for these two highly affected sectors are significantly related for a large part of rolling regressions and more strongly so during the earlier periods. More precisely, the positive association between telecommunications and news tone occurs for all rolling regressions up to mid-June, showing that telecommunications exhibit significant results 59% of the time, more frequently than any other sector. Durables, on the other hand, show a significant relation 43% of the time with the highest significance reached at the window ending on April 23. The news tone reaches the peak of its impact on energy, the second most negatively affected sector, on June 12. For brevity, we only graph the patterns for the two main sectors affected inversely.

Figure 1: Time Variation in t-Statistics



Note: This figure plots the t-test statistics for sectors of consumer durables and telecommunications based on each 60-day rolling window that ends on dates shown on the horizontal axis. Durbl (in blue) and Telcm (in red) represent durables and telecommunications sectors, respectively. The first rolling window ends on April 15 and the total sample utilized starts from 21 January to 31 July 2020.

Overall, our results suggest that the tone of news releases from the WHO impacts most industry returns significantly. While more negative news issued by the WHO translates into bad news for consumer durables, manufacturing, energy, and other industries, it shows to be good news for consumer nondurables, telecommunications, and healthcare sectors. The effect of news tone varies in significance and magnitude across sectors and over time as well.

4. Conclusion

Tone in WHO news releases during the COVID-19 pandemic contains information for different industries. We add to the literature in three main ways. First, we conduct textual analysis to quantify the tone of news releases published by the WHO. Second, we show that our tone measure is significantly related to returns for the majority of industries and that various industries react differently to it. Third, the relation between news tone and industries exhibits variation throughout the COVID-19 period.

Finally, there are other directions worth researching in the future. For instance, there is value in checking for other forms of portfolio sorting, using either different firm characteristics or criteria such as ESG ranking. In addition, the relation between news tone and stock returns can have the opposite impact on individual firms within the same sector, making us observe solely the average of these individual effects at the sector level. Thus, it would be interesting to conduct a study at the firm level as more data becomes available. We also encourage future research to benefit from our work and replicate our approach to capture the importance of tone in the announcements of other organizations such as CDC (Centers for Disease Control and Prevention) during health-related crisis. Overall, as investors revise their expectations based on past recessions, it is important to thoroughly analyze WHO news releases as a major news source during and after a health crisis–triggered recession.

References

Ahmad, K., Han, J., Hutson, E., Kearney, C., Liu, S., 2016. Media-expressed negative tone and firm-level stock returns. Journal of Corporate Finance 37, 152-172.

Baker, S. R., Bloom, N., Davis, S. J, Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. Review of Asset Pricing Studies 10, 742-758.

Bianchi, F., 2020. The Great Depression and the Great Recession: A view from financial markets. Journal of Monetary Economics 114, 240-261.

Ding, D., Guan, C., Chan, C. M., Liu, W., 2020. Building stock market resilience through digital transformation: Using Google trends to analyze the impact of COVID-19 pandemic. Frontiers of Business Research in China 14, 1-21.

Dzielinski, M., Hasseltoft, H., 2013. Aggregate news tone, stock returns, and volatility. University of Zurich, Working Paper.

Erdem, O., 2020. Freedom and stock market performance during COVID-19 outbreak. Finance Research Letters 36, Article 101671.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Ferguson, N. J., Philip, D., Lam, H., Guo, J. M., 2015. Media content and stock returns: The predictive power of press. Multinational Finance Journal 19, 1-31.

Garcia, D., 2013. Sentiment during recessions. Journal of Finance 68, 1267-1300.

Goodell, J. W., 2020. COVID-19 and finance: Agendas for future research. Finance Research Letters 35, 101512.

Groß-Klußmann, A., Hautsch, N., 2011. When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. Journal of Empirical Finance 18, 321-340.

Haroon, O., Rizvi, S. A. R., 2020. COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. Journal of Behavioral and Experimental Finance 27, Article 100343.

He, P., Sun, Y., Zhang, Y., Li, T., 2020. COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market. Emerging Markets Finance and Trade 56, 2198-2212.

Heston, S. L., Sinha, N. R., 2017. News vs. sentiment: Predicting stock returns from news stories. Financial Analysts Journal 73, 67-83.

Kuznetsova, L., .2020. COVID-19: The world community expects the World Health Organization to play a stronger leadership and coordination role in pandemics control. Front. Public Health. Available at https://doi.org/10.3389/fpubh.2020.00470.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. Journal of Finance 66, 35-65.

Ramelli, S., Wagner, A. F., 2020. Feverish stock price reactions to COVID-19. Review of Corporate Finance Studies 9, 622-655.

Shearer,E., 2020. Local news is playing an important role for Americans during COVID-19 outbreak. Available at https://www.pewresearch.org/fact-tank/2020/07/02/local-news-is-playing-an-important-role-for-americans-during-COVID-19-outbreak/.

Smales, L. A., 2021. Investor attention and the response of US stock market sectors to the COVID-19 crisis. Review of Behavioral Finance 13, 20-39.

Taylor T., Heath, T., 2020. Dow enters bear market after coronavirus declared pandemic. Available at https://www.washingtonpost.com/business/2020/03/11/markets-economy-today-oil-coronavirus/.

Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139-1168.

What has the World Health Organization done for us? Nat Microbiol 5, 977 (2020). Available at https://doi.org/10.1038/s41564-020-0772-3.

Appendix

Table A.1: Impact of News Tone and new COVID-19 Cases on Different Industries

	β_{MKT}	β_{SMB}	β_{HML}	β_{Att}	β_{NC}	β_{Tone}
NoDur	0.7937 ***	-0.0871 ***	0.1228 ***	0.5462 ***	-0.2680 ***	3.3545 ***
Durbl	1.1360 ***	0.3908 ***	0.0988 ***	-1.7468 ***	-0.5986 ***	-14.9096 ***
Manuf	1.0408 ***	0.0791 ***	0.4434 ***	1.2492 ***	-0.5887 ***	-1.0538 ***
Enrgy	1.1712 ***	0.2678 ***	0.8079 ***	0.7759 ***	-0.2648 ***	-10.4753 ***
Chems	0.8621 ***	-0.2175 ***	0.1600 ***	1.8326 ***	-0.0251	-0.2414
BusEq	1.1145 ***	0.0087 *	-0.3467 ***	-0.6060 ***	0.1167 ***	-0.2233
Telcm	0.8073 ***	-0.0394 ***	0.1708 ***	0.4143 ***	0.7419 ***	5.2102 ***
Utils	0.9814 ***	-0.2795 ***	0.1995 ***	0.8134 ***	0.1913 ***	-0.8909 ***
Shops	0.8597 ***	0.0376 **	-0.2847 ***	-0.5810 ***	0.0003	-0.2483 *
Hlth	0.8949 ***	-0.0638 ***	-0.2482 ***	1.0670 ***	0.0108	2.2084 ***
Money	1.1005 ***	-0.1050 ***	0.6253 ***	0.0449	-0.0027	-0.0029
Other	0.9243 ***	0.1974 ***	0.2848 ***	0.1065 **	-0.3524 ***	-2.0983 ***

Note: This table presents for each industry listed in the first column the average factor loadings from the following revised version of Equation (1). In addition to the Fama and French factors, attention, and news tone variables, the coefficient estimates for change in new COVID-19 cases, denoted by NC, are also included. The coefficient estimates are obtained from 60-day rolling windows of observations during our sample period of 21 January 2020 – 31 July 2020. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

$$R_{j,t} = \alpha_j + \beta_{MKT,j}MKT_t + \beta_{SMB,j}SMB_t + \beta_{HML,j}HML_t + \beta_{Att,j}Att_t + \beta_{NC,j}NC_t + \beta_{Tone,j}Tone_t + \varepsilon_t$$

APPLIED FINANCE LETTERS

VOLUME 10, 2021

IMPACT OF COVID-19 ON CRYPTOCURRENCIES: EVIDENCE ON INFORMATION TRANSMISSION THROUGH ECONOMIC AND FINANCIAL MARKET SENTIMENTS

Irfan Haider Shakri[1], Jaime Yong[1], Erwei Xiang[1]

1. Edith Cowan University, Australia

* Corresponding Author: Irfan Haider Shakri, School of Business and Law, Edith Cowan University, Western Australia, ✉ Email: irfanshakri@gmail.com

Abstract

This paper investigates the relationship between the COVID-19 crisis and the two leading cryptocurrencies, Bitcoin and Ethereum, from 31 December 2019 to 18 August 2020. We also use an economic news sentiment index and financial market sentiment index to explore the possible mechanisms through which COVID-19 impacts cryptocurrency. We employ a VAR Granger Causality framework and Wavelet Coherence Analysis and find the cryptocurrency market was impacted in the early phase of the sample period through economic news and financial market sentiments, but this effect diminished after June 2020.

Keywords: Cryptocurrency, COVID-19, economic news sentiment, VIX, VAR Granger causality, Wavelet Coherence Analysis

1. Introduction

The cryptocurrency market is dominated by Bitcoin and Ethereum, each representing 65% and 14% of a USD941 billion market capitalization respectively. During the start of the COVID-19 outbreak worldwide, both currencies lost almost half of their value within days - Bitcoin observed a decrease from USD9,000 to USD5,000 in the first two weeks of March 2020. This study focuses on the price behaviour of the two leading cryptocurrencies and how this market reacted to a significant systemic risk event given the widespread coverage of the crisis in the media and heightened levels of financial market uncertainty.

Behavioural finance literature suggests the impact of news sentiment can influence investment behaviour (Da, Engelberg, & Gao, 2015). Smales (2017) studied the importance of fear sentiment on the equity market returns and find significant effects. Further, market volatility measured with the VIX has greater influence on market returns during recessions. Li, Tian, Ouyang, and Wen (2020) concur, concluding that positive and negative sentiments lead to rises and falls in the returns of Chinese equity markets. Nițoi and Pochea (2020) examined the European markets using contagion and time-varying analysis and concluded that investors' perceptions are an important channel for the movement of markets in any direction, especially during times of crisis and economic uncertainty. Hence, there is ample literature to support the notion that financial markets are prone to move according to the sentiments of the investors, especially in the crisis situations.

Apart from equity markets, other studies have also been carried out to investigate the impact of the spread of COVID-19 crisis on the price behaviour of cryptocurrencies (Conlon & McGee, 2020; Corbet, Larkin, & Lucey, 2020; Mnif, Jarboui, & Mouakhar, 2020). However, the studies carried out on the behaviour of cryptocurrencies at the onset of the pandemic could not address the transmission patterns of COVID-19 onto the cryptocurrency market. Gurdgiev, O'Loughlin, and Chlebowski (2019) studied the behaviour of cryptocurrency market and find herding behaviour during times of crisis driven by fear and uncertainty. Chen, Liu, and Zhao (2020) also presented that cryptocurrency market is affected during the COVID-19 pandemic due to the fear sentiment. Similar conclusions have been drawn by other studies as well (Shahzad, Bouri, Roubaud, Kristoufek, & Lucey, 2019; Smales, 2019). This study considers the linkages and information flow from the rise in new cases and reported deaths each day on the cryptocurrency market through two channels: economic news sentiment and financial market sentiment.

In this paper, we use the economic news sentiment (ENS) index constructed by Shapiro, Sudhof, and Wilson (2020) to gauge public sentiment on economic news and the equity market volatility (VIX) index to measure financial market sentiment. In the initial months of the pandemic, new cases/deaths rose sharply worldwide along with the number of mortalities. The negative economic and financial news sentiment influenced the performance of financial markets including cryptocurrencies (Chen et al., 2020; Kang, McIver, & Hernandez, 2019). Amidst the crisis, several studies have been conducted to empirically test the impact of COVID-19 on several financial assets, their volatility and risks (Ali, Alam, & Rizvi, 2020; Chen et al., 2020; Zaremba, Szyszka, Long, & Zawadka, 2020). Our study aims to examine news sentiment (ENS) and equity market volatility (VIX) as paths or channels that impact of Bitcoin and Ethereum price behaviour during the spread of the pandemic using vector autoregression (VAR), Granger causality and wavelet coherence analysis (WCA).

2. Data, Sample and Research Design

Bitcoin and Ethereum daily prices were extracted from www.coindesk.com for a sample period from 31 December 2019 to 18 August 2020[1]. The daily data of the volatility index (VIX) was extracted from Thomson Reuters Eikon following the literature (e.g. (Akdağ, Kiliç, & Yildirim, 2019; Albulescu, 2020)). The number of coronavirus cases and the number of coronavirus deaths reported daily was collected from the World Health Organization's website. We use the ENS data compiled by Shapiro et al. (2020)[2] using positive and negative sentiments. The ENS index is compiled based on lexical analysis from economics-related news articles and is presented as sentiment scores drawn from a range of US published news with themes directly relating to "economics" and "United States". This ENS index has been utilized in a number of studies to test the impact of sentiment on risk and returns (Calomiris & Mamaysky, 2019) and economic activity (Benhabib & Spiegel, 2019). It has also been useful as a measure to capture sentiment at the onset of the global spread of COVID-19 (Aguilar, Ghirelli, Pacce, & Urtasun, 2020).

2.1 VAR Granger Causality

Granger (1969) statistically explained that a cause (x) occurs before its effect (y) and knowledge of a cause (x_{t-j}) improves the prediction of its effect. Following is the econometric explanation of the model used:

$$C_t = \alpha + \sum_{i=1}^{m} \beta_i C_{t-i} + \sum_{j=1}^{n} \gamma_j P_{t-j} + \sum_{k=1}^{q} \theta_k VN_{t-k} + \varepsilon_t$$

[1] The sample period's end date of 18 August 2020 was chosen to isolate the ENS index from the effects of the US 2020 elections. The formalisation of the presidential candidates for both parties took place at this time.

[2] See: https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

$$P_t = \alpha + \sum_{j=1}^{n} \gamma_j P_{t-j} + \sum_{i=1}^{m} \beta_i C_{t-i} + \sum_{k=1}^{q} \theta_k VN_{t-k} + \varepsilon_t$$
$$VN_t = \alpha + \sum_{k=1}^{q} \theta_k VN_{t-k} + \sum_{j=1}^{n} \gamma_j P_{t-j} + \sum_{i=1}^{m} \beta_i C_{t-i} + \varepsilon_t \tag{1}$$

where, C_t and C_{t-i} denote daily changes to the natural logarithm of cryptocurrency prices namely, Bitcoin (*BTC*) and Ethereum (*ETH*) at time t and its lagged values at time $t-i$ respectively. Daily changes to the natural logarithm of reported COVID-19 cases/deaths reported worldwide is represented as P_t and P_{t-j} for up to j number of lags. The *VIX* and *ENS* are represented in the vector denoted VN_t and VN_{t-k} for up to k lags. β_i, $\gamma_j$and θ_k are the factor loadings for the cryptocurrency, new COVID-19 cases/deaths, VIX and ENS, respectively. α is a constant term and ε_t is a mean stationary error term resembling white noise.

2.2 Wavelet Coherence Analysis (WCA)

Wavelet coherence analysis (WCA) has emerged in popularity to study the co-movement of time series variables, especially for the analysis of cryptocurrencies (Choi, 2020; Demir, Bilgin, Karabulut, & Doker, 2020; Goodell & Goutte, 2020). Our earlier analysis only allows us to establish if there is a transmission relationship between variables, but WCA allows us to look deeper into the timing of the effects. WCA plots the data into its frequency and time axes by rescaling the series (Crowley, 2007). This technique transforms a data series observed in discrete intervals into continuous waves to represent a continuous signal. The continuous wavelet transformation of a time series x(*t*) is calculated as:

$$W_{x(\tau,s)} = \int_{-\infty}^{\infty} x\,(t)\,\tilde{\psi}^{*}_{\tau,s}\,(t)\,dt \tag{2}$$

where, W_x is the continuous wavelet transformation of a time series x, τ is the control parameter for wavelet in time, *s* is the scaling parameter to determine the size of the wavelet, ψ is the mother wavelet, and $\tilde{\psi}^{*}_{\tau,s}\,(t)$ is the complex conjugate function. Based on the cross wavelet transform, the coherence of the wavelets is given by (Torrence & Webster, 1999):

$$R_{xy} = \frac{|S(W_{xy})|}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}} \tag{3}$$

where, R_{xy} is the correlation coefficient (localized correlation coefficient in frequency-time space), *S* is the smoothing operator in time and frequency, W_x and W_y are the wavelets for each time series and W_{xy} is the cross wavelet.

3. Empirical Results

3.1 VAR Granger Causality Results

The pre-requisite before running the VAR model is stationarity of the variables. We used several methods for testing the stationarity of the variables, the results are not presented due to brevity. Table 1 provides the results of our VAR estimations. Based on the *t*-statistics, our findings suggest that changes to Bitcoin and Ethereum prices are not directly influenced by changes to daily case numbers/deaths (Iqbal, Fareed, Wan, & Shahzad, 2020). Instead, reports of new cases/deaths impact ENS over this period and hence the transmission of public sentiment regarding reports of growing numbers of new cases/deaths onto the cryptocurrency market is observed. There is also a unidirectional effect of market volatility on news sentiment, which suggests that while financial markets were reacting to increased volatility during this period, this may have further amplified changes to sentiment relating to the economic impact of the health pandemic. We also find significant impact of the VIX on cryptocurrency returns, as heighted volatility in financial markets may lead investors to seek 'safe haven' assets, in which cryptocurrencies have recently been regarded as.

Table 1: VAR Results for Bitcoin and Ethereum

Panel A	***D(lnBTC)***	***D(ENS)***	***D(lnCASES)***	***D(VIX)***	***D(lnETH)***	***D(ENS)***	***D(lnCASES)***	***D(VIX)***
D (lnBTC (-1))	-0.02	-0.014	0.001	-6.635				
D (lnETH (-1))					-0.067	0.004	-0.076	-3.676
D (ENS (-1))	0.387**	0.289***	-0.388	3.396	0.493**	0.281***	-0.333	3.773
D (lnCASES (-1))	-0.015	0.012***	-0.218***	0.34	-0.011	0.012***	-0.217***	0.321
D (VIX (-1))	-0.002***	-0.004***	0.001	-0.198***	-0.004***	-0.001***	0.000	-0.201***
C	0.004	-0.002***	0.071***	0.055***	0.007***	-0.002***	0.072***	0.063
R^2	0.217	0.159	0.047	0.043	0.977	0.996	0.950	0.996
Adj. R^2	0.203	0.144	0.030	0.026	0.976	0.996	0.948	0.996
Sum Sq. Rsd.	0.279	0.036	10.332	7407.21	0.438	9.211	7120.17	0.032
Panel B	***D(lnBTC)***	***D(ENS)***	***D(lnDEATHS)***	***D(VIX)***	***D(lnETH)***	***D(ENS)***	***D(lnDEATHS)***	***D(VIX)***
D (lnBTC (-1))	-0.031	-0.021	-0.146	-9.057				
D (lnETH (-1))					-0.071	0.004	-0.067	-3.675
D (ENS (-1))	0.506***	0.316***	0.098	12.317	0.536**	0.290***	0.633	3.121
D (lnDEATHS (-1))	0.023	0.017**	0.155	2.518	0.016	0.002	0.609***	1.083
D (VIX (-1))	-0.002***	-0.001***	-0.000	-0.214***	-0.004***	-0.004***	0.000	-0.201***
C	0.002	-0.000	0.008**	0.02	0.005**	-0.001**	0.025***	0.021
R^2	0.234	0.171	0.708	0.068	0.247	0.132	0.367	0.042
Adj. R^2	0.205	0.14	0.696	0.033	0.233	0.116	0.355	0.025
Sum Sq. Rsd.	0.266	0.03	0.825	7202.3	0.464	0.032	1.785	7402.2

Note: This table presents the results of the VAR estimation (using two different measures of COVID – 19 spread intensities in Panel A and Panel B) on first differences from Equation [1]. lnBTC represents the log of Bitcoin prices, lnETH represents the log of Ethereum prices, lnCASES is the log of new COVID-19 cases reported each day, VIX is the volatility index and ENS is the Economic News Sentiment Index. *, ** and *** represent significance at 10%, 5% and 1% respectively.

While the initial VAR estimations first assume all variables are endogenous to the system of information transmission, we use the VAR Granger causality/ Block Exogeneity Wald test to further determine on a multivariate basis, the extent to which one variable Granger-causes another (see Table 2). Analysis presented in Table 1 and Table 2 using two separate measures of coronavirus cases and deaths report similar results. Our further analysis will focus on the number of cases due to two reasons. First, most countries followed a zero-transmission model in the early days of the pandemic where the focus was on daily infection numbers and this is captured in our sample period. Second, infection numbers may be more relevant than death numbers partly because infection numbers were more likely to cause panic at the time due to many unknowns about COVID at earlier stages and partly because deaths were largely amongst the elderly and people with other pre-existing conditions.

Table 2: VAR Granger causality/Block Exogeneity Wald Test Results

Dependent variable: *D(lnBTC)*			**Dependent variable: *D(lnETH)***		
Excluded	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$	***Excluded***	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$
D(ENS)	4.973**	6.53**	D(ENS)	4.68385**	4.333
D(lnCASES)/D(lnDEATHS)	2.028	0.868	D(lnCASES)/D(lnDEATHS)	0.61868	1.718
D(VIX)	54.32	51.72***	D(VIX)	65.26***	61.913***
All	60.968***	59.38***	All	70.3***	67.823***
Dependent variable: *D(ENS)*			**Dependent variable: *D(ENS)***		
Excluded	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$	***Excluded***	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$
D(lnBTC)	0.479***	0.812	D(lnETH)	0.06015	0.36
D(lnCASES)/D(lnDEATHS)	11.104***	7.928**	D(lnCASES)/D(lnDEATHS)	10.76***	8.328***
D(VIX)	11.372***	11.46***	D(VIX)	12.06***	12.4***
All	24.01***	21.79***	All	23.54***	21.29***
Dependent variable: *D(lnCASES)/D(lnDEATHS)*			**Dependent variable: *D(lnCASES)/D(lnDEATHS)***		
Excluded	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$	***Excluded***	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$
D(lnBTC)	0.000	1.503	D(lnETH)	0.07646	2.305
D(ENS)	0.135	2.333	D(ENS)	0.09717	2.378
D(VIX)	0.019	0.223	D(VIX)	0.02572	0.421
All	0.154	3.35	All	0.23090	4.159
Dependent variable: *D(VIX)*			**Dependent variable: *D(VIX)***		
Excluded	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$	***Excluded***	$X^2_{(lnCASES)}$	$X^2_{(lnDEATHS)}$
D(lnBTC)	0.46	2.074	D(lnETH)	0.24312	0.475
D(ENS)	0.014	2.038	D(ENS)	0.01737	2.91
D(lnCASES)/D(lnDEATHS)	0.037	0.371	D(lnCASES)/D(lnDEATHS)	0.03342	0.438
All	0.486	5.637	All	0.26894	4.01

Note: This table presents the results of VAR Granger Causality/Block Exogeneity Wald Test for Bitcoin and Ethereum against two separate measures for COVID – 19 intensities i.e., number of cases and number of deaths during the sample period. The null hypothesis of the test is that the lagged coefficients = 0, i.e., that variable x does not Granger-cause variable y. The results are presented for individual and joint associations for all variables. *, ** and *** represent significance at 10%, 5% and 1% respectively.

The Forecast Error Variance Decomposition (FEVD) results in Table 3 show that up to 20% of the variance in the forecast error of Bitcoin returns can be explained by a unit shock in changes to the VIX index. However, ENS has a greater impact (approximately 22%) on the forecast error of changes to Ethereum prices. From the VAR system of Bitcoin, we detect larger explanatory effects from market volatility and COVID-19 on news sentiment compared to the system with Ethereum, and suggest that findings related to Bitcoin are more informative, due to the dominance of this cryptocurrency in its market. While the FEVD for VIX indicates notable explanatory power of a unit shock in cryptocurrency returns and new COVID-19 cases, this is not supported in terms of market dynamics uncovered from our earlier analysis. We do not elaborate on the forecast error of new COVID-19 cases, as it is not meaningful.

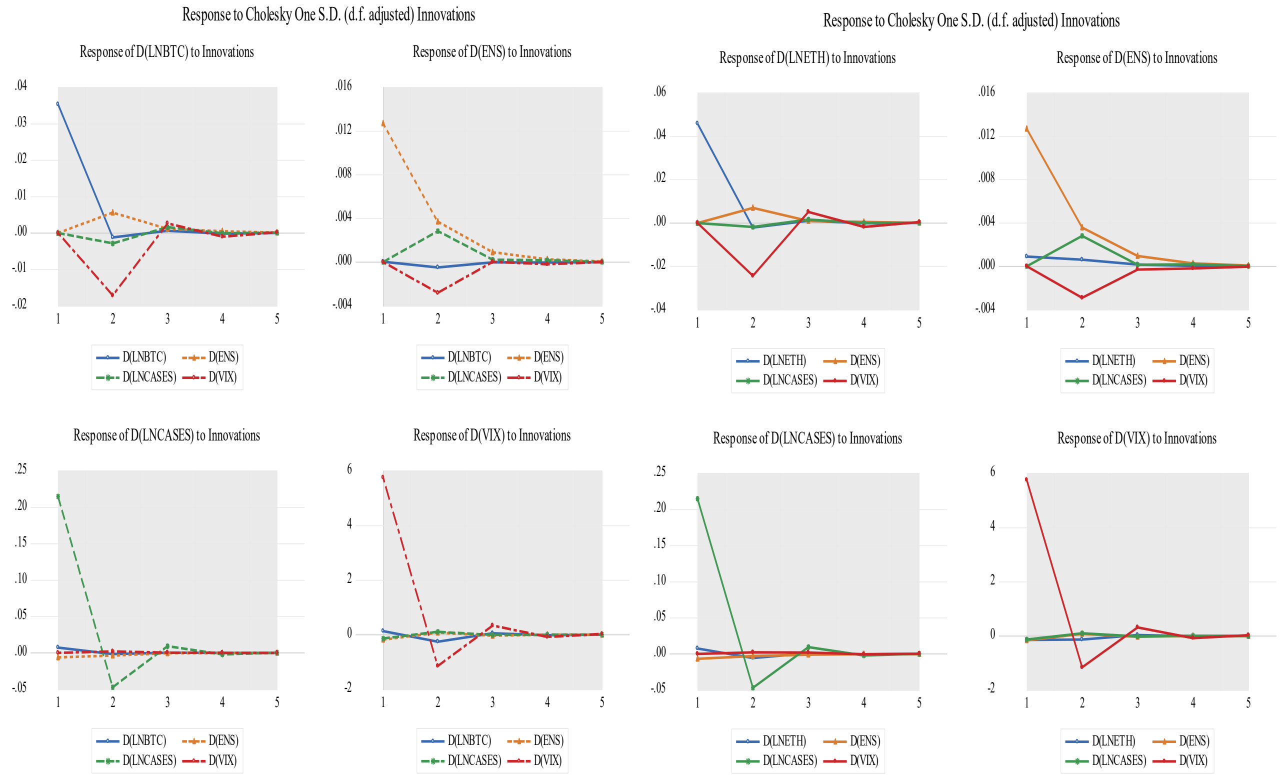
Table 3: VAR Variance Decomposition Model

Variance Decomposition of D(lnBTC)						Variance Decomposition of D(lnETH)					
Period	S.E.	D(lnBTC)	D(lnCASES)	D(VIX)	D(ENS)	Period	S.E.	D(lnETH)	D(lnCASES)	D(VIX)	D(ENS)
1	0.0353	100.00	0.0000	0.0000	0.0000	1	0.0459	100.00	0.0000	0.0000	0.0000
2	0.0398	78.943	0.5802	18.946	1.5291	2	0.0525	76.581	1.7830	0.1160	21.519
3	0.0400	78.416	0.7267	19.237	1.6198	3	0.0528	75.783	1.7989	0.2081	22.209
4	0.0400	78.352	0.7265	19.290	1.6296	4	0.0528	75.683	1.8070	0.2080	22.301
5	0.0400	78.350	0.7272	19.292	1.6301	5	0.0528	75.679	1.8071	0.2084	22.304
Variance Decomposition of D(lnCASES)						**Variance Decomposition of D(lnCASES)**					
Period	S.E.	D(lnBTC)	D(lnCASES)	D(VIX)	D(ENS)	Period	S.E.	D(lnETH)	D(lnCASES)	D(VIX)	D(ENS)
1	0.2152	0.0008	0.0808	0.1074	99.810	1	0.0127	0.5065	99.493	0.0000	0.0000
2	0.2203	0.1241	3.9907	4.6188	91.266	2	0.0138	0.6236	90.861	4.1102	4.4047
3	0.2205	0.1236	3.9905	4.5982	91.287	3	0.0138	0.6336	90.840	4.0975	4.4285
4	0.2205	0.1243	3.9999	4.6160	91.259	4	0.0138	0.6342	90.809	4.1102	4.4455
5	0.2205	0.1243	4.0001	4.6159	91.259	5	0.0138	0.6342	90.809	4.1102	4.4458
Variance Decomposition of D(VIX)						**Variance Decomposition of D(VIX)**					
Period	S.E.	D(lnBTC)	D(lnCASES)	D(VIX)	D(ENS)	Period	S.E.	D(lnETH)	D(lnCASES)	D(VIX)	D(ENS)
1	5.7633	0.1175	99.8824	0.0000	0.0000	1	0.2152	0.1242	0.0935	99.782	0.0000
2	5.8828	0.1169	99.8233	0.0093	0.0502	2	0.2203	0.1818	0.1060	99.701	0.0105
3	5.8926	0.1171	99.822	0.0094	0.0504	3	0.2205	0.1840	0.1082	99.689	0.0179
4	5.8932	0.1171	99.822	0.0094	0.0505	4	0.2205	0.1843	0.1083	99.688	0.0186
5	5.8933	0.1171	99.822	0.0094	0.0505	5	0.2205	0.1843	0.1083	99.688	0.0188
Variance Decomposition of D(ENS)						**Variance Decomposition of D(ENS)**					
Period	S.E.	D(lnBTC)	D(lnCASES)	D(VIX)	D(ENS)	Period	S.E.	D(lnETH)	D(lnCASES)	D(VIX)	D(ENS)
1	0.0127	0.0510	0.0569	99.891	0.0000	1	5.7661	0.0642	0.0761	0.0560	99.803
2	0.0138	0.2415	0.0832	99.669	0.0053	2	5.8842	0.1132	0.0906	0.0807	99.715
3	0.0138	0.2501	0.0830	99.658	0.0080	3	5.8927	0.1165	0.0927	0.0813	99.709
4	0.0138	0.2508	0.0831	99.657	0.0080	4	5.8933	0.1168	0.0928	0.0813	99.709
5	0.0138	0.2508	0.0831	99.657	0.0080	5	5.8933	0.1168	0.0928	0.0813	99.709

Note: This table presents the VAR Variance Decomposition Model for all the variables used in this study both with the Bitcoin prices and Ethereum prices. LnBTC indicates log of Bitcoin prices; lnETH indicated log of Ethereum prices; lnCASE represents the number of cases reported during COVID-19; VIX represents the volatility index and ENS is the economic news sentiment.

The impulse response functions of Figure 1 shows that an upward shock up to one standard deviation (innovations) in cryptocurrency returns leads to an immediate increase in next day returns, and the effect starts to diminish then dissipate after 2 days. The impact of a shock to changes in ENS causes an initial increase to cryptocurrencies for 2 days, after which it starts to decrease and dissipate by the third day. In contrast, an initial upward shock in the VIX results in a negative response for cryptocurrencies for up to 2 days but reverses and the effects do not persist for more than 4 days. Comparatively there is very little response in cryptocurrencies from shocks to new daily coronavirus cases. Innovations to one-period lagged changes to ENS causes an initial increase to current sentiment, and the effects start to diminish but can remain persistent for up to 4 days. We also find a positive one standard deviation shock to new coronavirus cases has an increasing impact on news sentiment for up to 2 days afterward, then diminishes and dissipates after the 3rd day. However, there is an inverse response to changes in news sentiment resulting from a positive shock to VIX but after 2 days this reverts and is no longer persistent after 3 days. The IRFs also show that there is little to no impact of innovations from the cryptocurrency markets, news sentiment or market volatility on new cases, as expected. VIX is also largely only impacted by innovations to its own past values.

Figure 1: Impulse Response of Bitcoin and Ethereum in response to one standard deviation shocks to the Economic News Sentiment, Volatility Index (VIX) and new daily COVID-19 cases reported during the period.

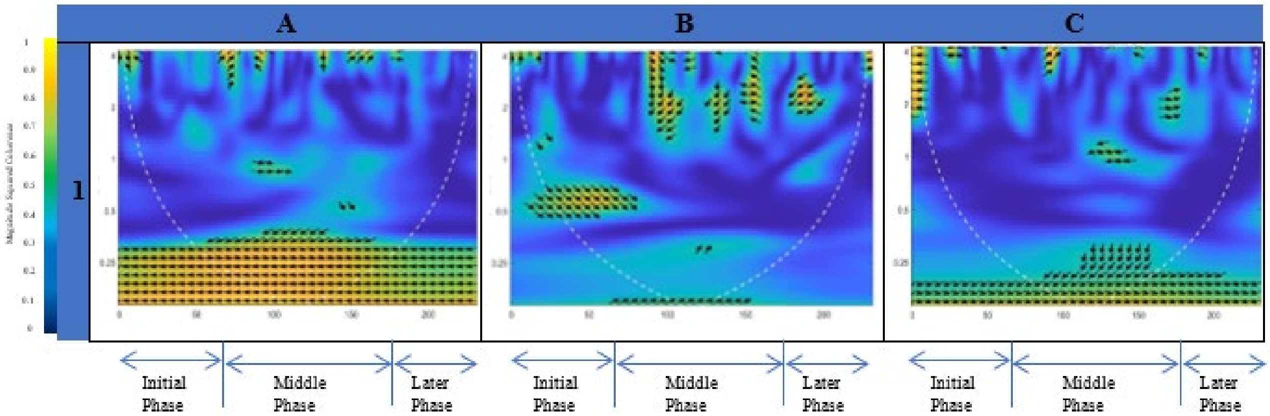


3.2 Wavelet Coherence Analysis Results

Before the application of WCA for Bitcoin and Ethereum prices, we first attempt to understand the information transmission flows of the other three variables i.e. daily cases of COVID-19, VIX and ENS. Extending from our previous analysis, we aim to determine how the responses of these variables to each other evolved over the eight months of our sample period in terms of their correlations and their lead/lag relations. We divided our sample period into three phases: **Initial phase** – the start of COVID-19, where first reports of cases found in China and sporadic cases found in some other countries, when there were no travel restrictions and no strict lockdowns imposed globally (*start to 28th February 2020);* **Middle phase** – reports of cases started to rise in other countries indicating the accelerating spread of the pandemic globally, when travel restrictions and strict lockdowns were imposed globally and new cases were on the rise (*March 01, 2020 to June 30, 2020)*, and **Later phase** – when most of the countries including Europe re-opened their borders but there was economic slowdown (*July 1, 2020 to August 18, 2020*).

From Figure 2 (1A) the wavelet coherence does not show any correlation between ENS and VIX in the initial phase of the sample period, as during this time the spread of the pandemic was limited to a few countries and there were no widespread reports globally. However, as we move forward on the timeline, the arrows within the cone of influence point leftward meaning that ENS and VIX were inversely related to each other during the middle phase with a high magnitude of correlation (shaded yellow). On the top side of the graph, some evidence of very high magnitude has been observed pointing right indicating that changes to the VIX index leads ENS during the middle phase. However, within the cone of influence, there is no evidence of high correlation between ENS and VIX during the later phase of the sample period. There is evidence of correlation between COVID-19 cases and ENS in Figure 3 (1B) with strong correlations in the initial and middle phases. However, no strong correlation has been observed between COVID-19 cases and VIX in Figure 3 (1C). These results are consistent with our previous analysis of VAR Granger Causality and Block Exogenous Wald test.

Figure 2: Wavelet Coherence Graphical Matrix

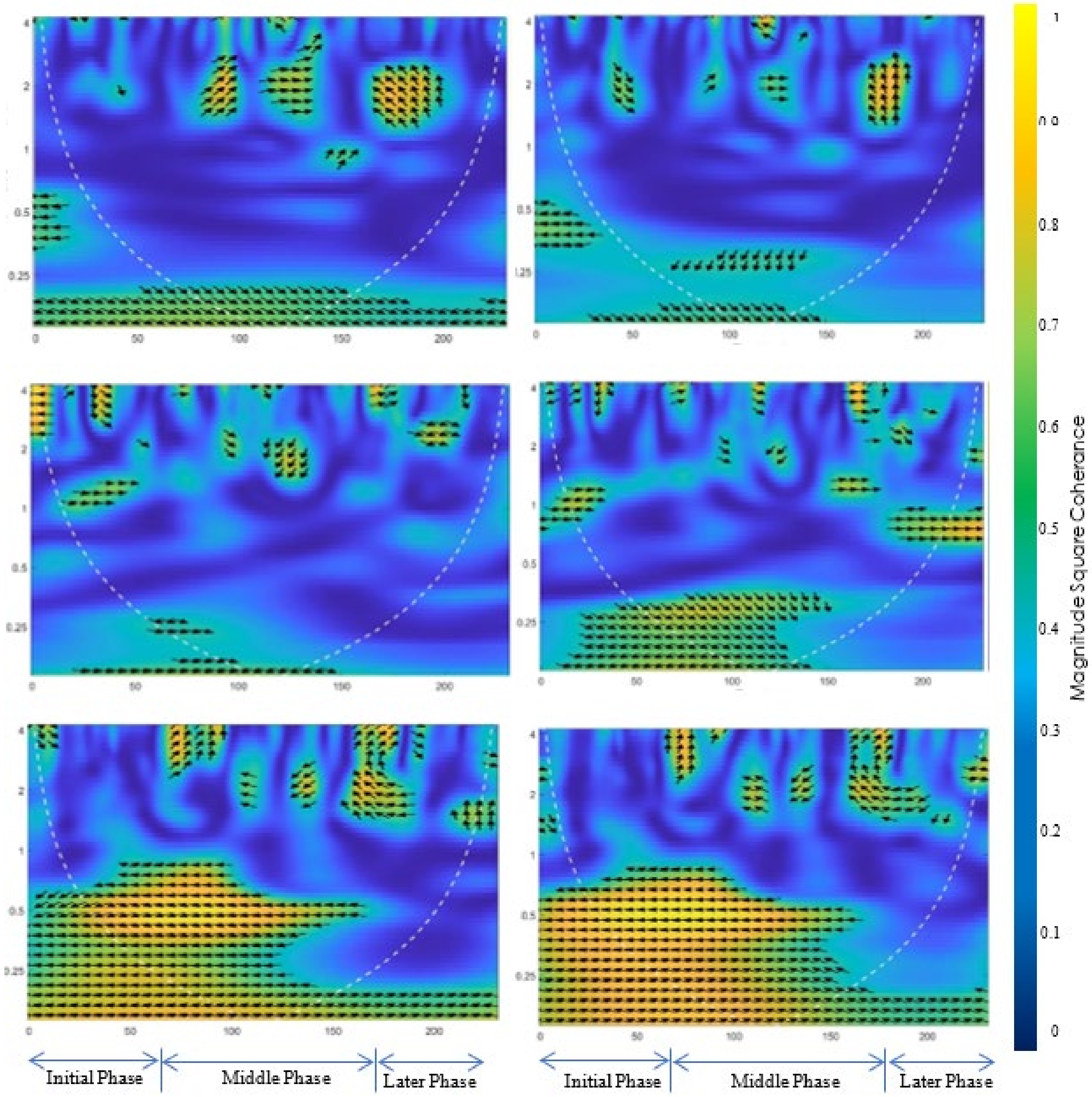


Note: In the above wavelet coherence graphical matrix, 1A represents the coherence of economic new sentiment (ENS) and equity market volatility index (VIX), 1B represents coherence between COVID-19 cases and ENS, and 1C represents the coherence between COVID-19 cases and VIX. The horizontal axis represents 'time (in days)' whereas the vertical axis represents the 'frequency (cycles/sample)'. On the left side of the matrix, the magnitude coherence scale is presented between 0 (blue) and 1 (yellow). The whole sample period is divided into three phases i.e. initial phases from start of the period until 28th February 2020, the middle phase – March 01, 2020 to June 30, 2020, and the later phase ranges from July 1, 2020 to August 18, 2020. Arrows indicate phase differences. Arrows pointing to the right show a positive correlation and vice versa. If the arrows point downwards, this means the first series leads the second one; if they point upwards, this means the second series leads the first one.

WCAs of COVID-19 cases, ENS and VIX with Bitcoin and Ethereum prices are presented in Figure 3 observe no signs of correlation between Bitcoin prices and COVID-19 cases in the initial phases (see Figure 3 (1A and 1B)) as compared to Ethereum that shows low correlation with COVID-19 cases in the initial phase. This may be due to the fact that Bitcoin is the leading cryptocurrency with higher capital flows and prices as compared to Ethereum. The upward arrows in the middle phase indicates COVID-19 cases have led fluctuations in Bitcoin prices but this was not dominant. In the later phase both Figures 4 (1A) and (1B) show strong correlation between prices of these currencies and COVID-19 cases. We can conclude that the spread of the pandemic has not predominantly or directly affected Bitcoin and Ethereum prices, as suggested by other similar studies (Choi, 2020; Goodell & Goutte, 2020).

Figure 3 (2A and 2B) shows no consistent signs of correlation throughout the initial, middle, and later phases have been observed for Bitcoin (see Figure 3 2A) and Ethereum (see Figure 3 2B) prices with ENS, rather, except for the Ethereum that has shown moderate correlation in the middle phase with ENS. A very strong and negative correlation between Bitcoin prices and VIX (Figure 3, 3A), and Ethereum and VIX (Figure 3, 3B) has been observed in the initial and middle phases. The equity market volatility led the cryptocurrency prices negatively during the initial and middle phases. However, the later phase has not observed any sign of strong correlation with VIX. Through all the observations, we conclude that the prices of the Bitcoin and Ethereum are mainly influenced by the information flow of COVID-19 cases to ENS and VIX during the initial and middle phases and then the rehabilitation process occurs in the later phases where no strong correlation was observed.

Figure 3: Wavelet Coherence Graphical Matrix



Note: In the above wavelet coherence graphical matrix, wavelet coherence analysis illustration has been presented as: 1A = Bitcoin prices and COVID-19 cases, 1B = Ethereum prices and COVID-19 cases, 2A = Bitcoin prices and ENS, 2B = Ethereum prices and ENS, 3A = Bitcoin prices and VIX, and 3C = Ethereum prices and VIX. The horizontal axis represents 'time (in days)' whereas the vertical axis represents the 'frequency (cycles/sample)'. On the right side of the matrix, the magnitude coherence scale is presented between 0 (blue) and 1 (yellow). The whole sample period is divided into three phases i.e. initial phases from start of the period until 28th February 2020, the middle phase – March 01, 2020 to June 30, 2020, and the later phase ranges from July 1, 2020 to August 18, 2020.

4. Conclusion

The first year of the global coronavirus pandemic has brought on an unprecedented level of economic and financial market uncertainty, due to the scope and speed of its spread and drastic responses to curb the rise of infection numbers. This paper provides some empirical evidence on the information transmission of COVID-19 to cryptocurrencies through economic news and financial market sentiments. VAR Granger Causality/Block Exogeneity Wald Test and Wavelet Coherence Analysis results show that new daily coronavirus cases reported, economic news sentiment and financial market volatility Granger-cause Bitcoin and Ethereum prices. Moreover, the WCA results further reveal that information transmissions flowed significantly during the initial and middle phases of the sample period. Taken together with our findings from impulse responses and variance decomposition, one standard deviation shocks to each explanatory variable can have a persistent effect on cryptocurrencies for up to 2 days and that the VIX Index has a more dominant effect on Bitcoin while ENS impacts Ethereum more significantly. Our study period covers the first 8 months of the unfolding COVID-19 health crisis, which has offered us a unique opportunity to study market reactions to the initial shock of the pandemic. As the global response to this health crisis continues to evolve, further study can be conducted on the transmission of information into cryptocurrencies and other financial assets.

Our findings contribute to the ongoing debate on cryptocurrencies being ‘safe havens’ in the times of crisis by studying the behaviour of the two top cryptocurrencies during the first year of the spread. Our findings suggest cryptocurrency is a viable asset class at the time of the health crisis and negative economic sentiment. The findings of this study have theoretical implications as they shed some light on the impact of systemic risk and how it transmits into financial assets through channels that measure market sentiment.

References

Aguilar, P., Ghirelli, C., Pacce, M., & Urtasun, A. (2020). Can news help measure economic sentiment? An application in COVID-19 times.

Akdağ, S., Kiliç, İ., & Yildirim, H. (2019). Does VIX scare stocks of tourism companies? Letters in Spatial and Resource Sciences, 12(3), 215-232.

Albulescu, C. (2020). Coronavirus and financial volatility: 40 days of fasting and fear. arXiv preprint arXiv:2003.04005.

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19)–An epidemic or pandemic for financial markets. Journal of Behavioral and Experimental Finance, 100341.

Benhabib, J., & Spiegel, M. M. (2019). Sentiments and economic activity: Evidence from US states. The Economic Journal, 129(618), 715-733.

Calomiris, C. W., & Mamaysky, H. (2019). How news and its context drive risk and returns around the world. Journal of Financial Economics, 133(2), 299-336.

Chen, C., Liu, L., & Zhao, N. (2020). Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The Case of COVID-19. Emerging Markets Finance and Trade, 56(10), 2298-2309.

Choi, S.-Y. (2020). Industry volatility and economic uncertainty due to the COVID-19 pandemic: Evidence from wavelet coherence analysis. Finance Research Letters, 37, 101783.

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Finance Research Letters, 35, 101607.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. Finance Research Letters, 35, 101554.

Crowley, P. M. (2007). A guide to wavelets for economists. Journal of Economic Surveys, 21(2), 207-267.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. The Review of Financial Studies, 28(1), 1-32.

Demir, E., Bilgin, M. H., Karabulut, G., & Doker, A. C. (2020). The Relationship between Cryptocurrencies and COVID-19 Pandemic. Available at SSRN 3585147.

Goodell, J. W., & Goutte, S. (2020). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. Finance Research Letters, 101625.

Gurdgiev, C., O'Loughlin, D., & Chlebowski, B. (2019). Behavioral Basis Of Cryptocurrencies Markets: Examining Effects Of Public Sentiment, Fear, And Uncertainty On Price Formation. Journal of Financial Transformation, 49, 110-121.

Iqbal, N., Fareed, Z., Wan, G., & Shahzad, F. (2020). Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. International Review of Financial Analysis, 73, 101613.

Kang, S. H., McIver, R. P., & Hernandez, J. A. (2019). Co-movements between Bitcoin and Gold: A wavelet coherence analysis. Physica A: Statistical Mechanics and its Applications, 536, 120888.

Li, Z., Tian, M., Ouyang, G., & Wen, F. (2020). Relationship between investor sentiment and earnings news in high-and low-sentiment periods. International Journal of Finance & Economics.

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. Finance Research Letters, 101647.

Nițoi, M., & Pochea, M. M. (2020). Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. Economic Modelling, 86, 133-147.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? International Review of Financial Analysis, 63, 322-330.

Shapiro, A. H., Sudhof, M., & Wilson, D. (2020). Measuring news sentiment.

Smales, L. A. (2017). The importance of fear: investor sentiment and stock market returns. Applied Economics, 49(34), 3395-3421.

Smales, L. A. (2019). Bitcoin as a safe haven: Is it even worth considering? Finance Research Letters, 30, 385-393.

Torrence, C., & Webster, P. J. (1999). Interdecadal changes in the ENSO–monsoon system. Journal of climate, 12(8), 2679-2690.

Zaremba, A., Szyszka, A., Long, H., & Zawadka, D. (2020). Business sentiment and the cross-section of global equity returns. Pacific-Basin Finance Journal, 101329.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

PRESENCE OF ANALYSTS BEFORE IPO AND UNDERPRICING: A META-ANALYSIS

Udayan Karnatak[1], Chirag Malik[1]

1. BML Munjal University

* Corresponding Author: Mr. Udayan Karnatak, PhD Scholar, School of Management, BML Munjal University, ✉ Email: udayan.karnatak@gmail.com

Abstract

In this study, the influence of analyst presence on underpricing produces a different outcome. We discover compelling evidence of the relationship between analyst presence and underpricing of IPOs by combining the results of twelve research involving over 20,400 businesses using meta-analysis. The IPO underpricing grows by 4.9 percent for every one percent increase in analyst presence. Furthermore, a meta-regression between impact magnitude and moderator factors revealed a substantial and favourable influence of a prominent underwriter in increasing the underpricing of the IPO followed by analysts. Our findings are particularly relevant for US market IPOs, as reputable underwriters operate as a moderator and considerably influence underpricing, calling into doubt the US authorities' control over pre-IPO research and attempts to reduce IPO mispricing. However, in emerging markets, underwriter reputation and syndicate have little influence on IPO underpricing.

Keywords: Analyst presence, Information asymmetry, Market efficiency, Underwriter's reputation, Underpricing

1. Introduction

In addition to the material supplied by the issuer firm in their prospectus for the IPO (initial public offering), security analysts supply information to the investors. Analysts' knowledge or signals must decrease information asymmetry and assist potential investors in determining the fair price of the IPO (Roulstone, 2003) and reduce underpricing (Muscarella and Vetsuypens, 1989). Even yet, underpricing is a regular occurrence in the IPO literature. We believe that the presence of analysts prior to the IPO listing improves information quality, sending favourable signals to potential investors. Their inclusion in the underwriter syndicate before to the IPO increases liquidity for the stock on the IPO listing day, albeit at the risk of underpricing or overpricing.

Underpricing is costly to the issuer business, and the issuer would prefer to avoid it through improved discussions with the issue's lead manager. As a result, by employing a renowned underwriter, the issuing business sends a signal of reduced uncertainty (Carter and Manaster, 1990). Underpricing, on the other hand, is the fault of respectable underwriters and their syndicate, which includes co-lead managers and analysts (Dimovski et al., 2010). In comparison to the non-US sample of research, we suggest that the presence of analysts in the underwriters' syndicate enhances investors' trust in the US IPO. Because US authorities prohibit early research and its dissemination to the public in order to minimize manipulations by the underwriters' syndicate, the presence of analysts prior to the issuance of the IPO instils trust in the investor, resulting in increased demand for the share on the IPO's listing day. In contrast, the presence of analysts had no influence on underpricing in the non-US sample.

The purpose of this article is to assess the impact of the IPO's pre-issue analyst presence on the IPO's early results. As a result, our research question is: What are the drivers of underpricing of shares in an IPO when analysts are present prior to the IPO's release? We utilized meta-analysis on the twelve papers to answer this question where one of the independent factors is the existence of an analyst prior to the issue and the dependent variable is underpricing and its influence on the variable "underpricing" was found In this study, the possible endogeneity between the variables underpricing and pre-issue analyst presence is not a reason for worry because underpricing of IPOs happens only on the first day of the IPO (Sahoo, 2014).

Daily et al. (2003) were the first to do a meta-analysis on underpricing in IPO research. More general determinants of underpricing were proposed in their work. Our method differs from theirs in that we have incorporated pre-issue analyst presence in the underwriter's syndicate, which is a new variable, and assess its impact on IPO underpricing in the meta-analysis methodology. We make two contributions to the literature. First, regardless of whether the sample is US or non-US (developing market), this study is a first attempt to assess the effect size of analyst presence and its relationship with IPO underpricing.

Second, Daily et al., (2003) evaluated the impact sizes of several factors on underpricing and concluded that these effect sizes were effective. We take a step further by including meta-regression into our investigation of the effect magnitude of analyst presence on underpricing. We have added variables in the meta-regression, such as industry dummy and age of issuing business, the assets and share overhang of the issuing firm, the underwriter repute, and the country dummy for US and developing market data. The moderating variables are selected based on their proximity to the presence of analysts covering the business. For example, an associated analyst typically covers the company from whom they receive positive information (Lin and McNichols, 1998). Such businesses have reputed underwriters insuring them, are mature in terms of age, and have significant asset values. As a result, it is necessary to control these factors and determine their moderating influence in order to explain the magnitude of the relationship between analyst presence and IPO underpricing.

The meta-analysis results reveal that there is a substantial and positive link between pre-issue analyst presence and underpricing, which is around 4.9 percent. The presence of security analysts prior to the release of a product causes underpricing and contradicts the idea that security analysts contribute to informational efficiency. According to this idea, the presence of high-quality analysts covering the firm's IPO prior to the issuance increases informational efficiency. Increased information quality caused by pre-issue analyst presence should eventually minimize underpricing on the first day of the sale.

Our study, on the other hand, asks a very pertinent question: "Why does pre-issue analyst presence raise money left on the table for the issuing firm?" We addressed this topic by splitting the sample into US and emerging market data and determining the magnitude of the effect of analyst presence on underpricing on both data sets. The positive, significant, and larger-than-average effect size of the US sample, indicating increased underpricing owing to the presence of analysts in the underwriter's syndicate, demonstrates information asymmetry in the US IPO markets. This is due to the restrictions imposed by US authorities on preliminary research.

Furthermore, meta-regression results reveal that underwriter reputation has a positive and substantial impact on effect magnitude, implying that underwriting reputation moderates the effect of pre-issue analyst presence and enhances underpricing for the IPOs covered by the analyst. For the research utilizing US data, the results show that IPO underwriter reputation is significant in attracting pre-issue analyst presence, which further enhances skewed pricing of an IPO on the first day of the offering. The existence of a renowned underwriter as a mediator between analyst presence and emerging market data is important for emerging market data. Furthermore, underpricing the IPO has a negligible negative impact. The findings show that the presence of a renowned underwriter in a developing market IPO reduces information asymmetry and enhances market efficiency, which helps the issuing business by preventing money from being left on the table.

The following is the structure of this document. Section 2 discusses the primary literature on underpricing and pre-issue analyst presence. Section 3 demonstrates the study's data gathering and methodology. Section 4 displays the findings of the meta-analysis. Section 4 discusses the outcome. Section 5 brings the research to a close.

2. Review of literature

The discrepancy between the offer price and the first day closing price of the share when it is traded in the secondary market is the underpricing of the shares issued in the original offering. On average, Reilly and Hatfield (1969), McDonald and Fisher (1972), and Bear and Curley (1975) found that initial public offerings performed well on the first day. Ibbotson (1975) discovered that the positive return on the first day was 11.4 percent, indicating that the IPO was underpriced. With the assumption of information asymmetry, Baron (1982) presented a model to explain the underpricing of the IPO. He ascribed the underpricing to the issuer's failure to oversee the underwriter's distribution activities, which results in lower offer prices on a listing day, resulting in underpricing.

Underpricing or anomalous first-day returns have been investigated as a predictive variable in the literature following the listing of the IPO (Rajan and Servaes (1997), Aggarwal et al (2002), Cliff and Dennis (2004), Gwilym and Verousis (2009), Bourzoita et al (2015)). Aside from that, another set of studies exists in which IPO underpricing is extensively investigated as a result of factors, for example, offer price changes, pre-issue analyst presence, underwriter preferences (agency problem), reputation and characteristics, venture capitalist presence, lead-manager reputation, star analyst presence, company industry characteristics (Cliff and Dennis (2004), Arnold et al, (2010), Adjasi et al (2011), Alanazi and Al-Zoubi (2015), Bradley et al (2015), Chourou et al (2018), Fullbrunn et al (2019), Jia et al (2019), Boulton et al (2020),).

According to Chang et al. (2016), the cause for IPO underwriting is an agency problem between the underwriter and the issuer. They emphasized the underwriter's authority as a result of the book building technique, in which they have complete control over the price. By displaying control, underwriters achieve their aim of attracting the most attention from institutional and retail investors for the IPO. Their gain is a decrease in subscription risk and an increase in commission by allocating underpriced shares to institutions or their clients (Loughran and Ritter, 2002).

Furthermore, by partially adjusting the offer price, underwriters attempt to reconcile the issuer's expectation of maximum issue proceeds with their own aims, as stated above. Benveniste and Spindt (1989) provided an alternative perspective on balance. They argue that underwriters analyze the IPO's demand with the aid of information providers on a certain offer price and then modify the price partially upwards to pass on the advantage to the issuer and the difference in the form of underpricing to provide the information providers monetary profits. Thus, underwriters are IPO price makers, and through underpricing, they achieve a variety of objectives, one of which is analyst coverage post-IPO.

The presence of top analysts and respected lead managers in the venture capital company also contributes to underpricing. The underwriting syndicate idea was proposed by Bradley et al. (2015). They discussed the relationship between the lead manager, co-manager, and underwriter and emphasized the ease with which businesses supported by prominent venture capitalists may obtain analyst presence when underpricing is high. Furthermore, the firm's IPO is underpriced if it is backed by top venture capitalists, indicating underplay between the underwriter and its associates, as observed by Liu and Ritter (2010) as a spinning hypothesis, and is consistent with the hot IPO chase by the star analyst, as proposed by Loughran and Ritter (2004) and further examined by Cliff and Denis (2004) and Liu and Ritter (2011).

In addition to post-IPO analyst coverage, which is a consequence of underpricing as represented in the analyst lust theory, pre-issue analyst coverage is another predictor of IPO underpricing in the literature. Jia, Xie, and Zhang (2014) discovered, using data from Chinese IPOs from 2006 to 2012, that pre-IPO research and coverage increases the likelihood of offer price adjustments and positive sentiment. The study's most interesting finding was a negative relationship between offer price revisions and first-day returns, which Jia et al. (2014) attributed to pro-rata allocation rules different from those used in US IPOs, which prohibit underwriters from allocating underpriced shares to their associates, ensuring that pre-IPO analyst research is fully incorporated into the IPO price.

The link between offer price revisions and underpricing is paradoxical due to varied IPO guidelines in developing and developed financial markets. As a result, it is worth noting the relationship between the presence of analysts in the underwriter's syndicate (covering the business before or post-IPO) and underpricing in both US and developing market studies.

Investors and financial markets benefit from the analyst role in information sharing. This is what one section of the literature claims. Ivakovic and Jegadeesh (2004), for example, argue that the analyst discovers the private information and analyses the released information. As a result, analysts create a more favorable information environment in which private and public information flows effectively from the firm to the investors. Another body of work challenges the information efficiency theory in relation to analysts. For example, both affiliated and unaffiliated analysts provide pre-issue IPO research and IPO presence. The presence of affiliated analysts covering the firm's pre-issue IPO may be owing to the underwriter's need, and therefore in the literature, it is clear that this presence might offer investors skewed signals.

According to Michaely and Womack (1999), underwriter analysts (associated analysts) offer more skewed signals to investors than unaffiliated analysts. Concurrent with this discovery, Degeorge (2007) stated that issuers pay for the positive presence of linked and unaffiliated analysts, resulting in skewed signals. As a result, unaffiliated analysts may contribute to the information inefficiency that affects IPO price discovery and may result in underpricing. Hence, the literature contains evidence of biased recommendations from both affiliated and unaffiliated experts.

He and Lin (2015) provided evidence of a reduction in information asymmetry as well as an improvement in information precision to support the information efficiency theory connected to analyst following. According to Baron, IPO underpricing is an anomalous event caused by the uncertainty produced by information asymmetry (1982). Underpricing is likely to reduce as a result of the pre-issue analyst involvement in the IPO. Sahoo (2014) examined 157 IPOs in India from 2007 to 2012 and discovered a negative link between IPO underpricing and analyst pre-issue IPO presence.

Jia et al. (2019) discovered, with identical results, that analysts' pre-issue presence reduces early returns. Wang (2008) compared underpricing in three different nations. They discovered less underpricing in Hong Kong IPOs when compared to US and Singapore IPOs, and they ascribed the difference to the fact that pre-issue IPO research is permitted in Hong Kong but not in the other two countries. Furthermore, Deng and Dorfleitner (2008) discovered a negative link between numerous co-lead managers covering the IPO and the IPO's first-day results. They claimed that increasing the presence of co-lead managers might reduce underpricing evidence by lowering the IPO's early returns.

Some evidence contradicts the unfavorable link between pre-IPO research and underpricing. According to Loughran and Ritter (2004) and Liu and Ritter (2011), the inclusion of star analysts and respected underwriters in the team causes the IPO to be underpriced. As a result of their findings, they provided the first proof of analyst lust theory, which explains the tendency of venture capital-backed businesses to have a thirst for star analyst coverage of an underpriced IPO. Kennedy et al. (2006) show that as the number of co-lead managers grows in IPOs, so does the underpricing. According to Loughran and Ritter (2004), co-lead managers are members of the underwriter's syndicate and offer research coverage for the IPO. As a result, their research coverage is biased toward the buy-side, creating upward momentum for the share price on the first day of trade, leading in IPO underpricing.

Jeon et al. (2015) discovered much decreased underpricing as a result of several underwriters handling the problem. They documented the idea in contrast to Hu and Ritter's (2007) tradeoff argument, which focuses on increasing the number of underwriters to enhance visibility at the expense of increasing underpricing. However, the amount of underpricing reported by them is proportional to the quantity of analysts covering the problem. Furthermore, Dambra et al. demonstrated an improvement in a firm's visibility at the expense of underpricing (2018). They contend that an increase in analyst pre-IPO presence enhances investor confidence, resulting in greater volume and price momentum post-IPO. Eventually, greater investor confidence leads to increased underpricing. Furthermore, Massa and Zhang (2020) demonstrated the favorable link between underpricing and the existence of a star analyst.

There is conflicting data about the relationship between pre-IPO analyst presence and underpricing. As a result, further research is required to answer the question: Is the presence of a pre-issue analyst significantly connected to underpricing? Is there a good or negative influence of pre-issue analyst presence on underpricing? Concurrent with these study questions, our research hypothesis is: “The existence of pre-issue analyst presence has an influence on underpricing.” Furthermore, we contend that underpricing caused by pre-issue analyst involvement is mitigated by underwriter repute and the presence of venture capitalists, the assets and age of the firm, the industry characteristics, and the nation from where the data was taken. In anticipation of future advantages, the firm's underwriter reputation draws analyst presence (Loughran and Ritter, 2004).

3. Data and methodology

3.1 Selection of data

Cooper (1982) recommended descendency technique is used by us. In this method, all of the articles that are cited central to the issue are retrieved and then evaluated for relevancy to the main concept. This procedure is repeated until the search is completed.

We examined three databases for relevant studies: Science Direct, Scopus, and Clarivate. The term "underpricing" yielded almost 2000 items across all three databases. The papers were then shortlisted based on these criteria:

1. Underpricing, first day returns or beginning returns are retained as a dependent variable in the model, whereas pre-issue analyst presence is an independent variable or belongs to a control group of variables.
2. To eliminate the publishing bias proposed by Cooper, studies are chosen regardless of the importance of the influence of the independent variable on the dependent variable (1982).
3. To reduce variability in the sample of research, we included equity IPOs but omitted SEO and REIT.

3.2 Sample Size

After applying the criteria, we chose twelve papers that matched the goal of the meta-analysis. In all of the research, the sample period begins in the year 2000.

3.3 Methodology

In this work, we have utilized meta-analysis to determine the cumulative effect size of pre-issue analyst presence as an independent variable on the dependent variable, IPO underpricing. The analysis of the analysis is known as meta-analysis (Glass, 1970). It is a quantitative approach for determining the empirical aggregate effect of a predictor variable on a dependent variable based on the findings of many studies. Furthermore, unlike qualitative evaluations, the technique successfully captures heterogeneity (Light, 1984). The aggregate link between the two variables is evaluated using the variable's correlation coefficient and the sign of the correlation coefficient in this technique. The Fisher's z-transformation method is used to convert the correlation coefficient to its impact magnitude (Hedges and Olkin, 1985). Another approach for determining effect magnitude is to compute the weighted mean of correlation coefficients (Hunter and Schimdt, 1990).

In this study, we are interested in the beta coefficients and t-values of the regression model that relates IPO underpricing with pre-issue analyst presence in various studies. For instance, a regression model is:

Underpricing = $\beta_0 + \beta_1 \times$ pre-issue analyst presence + e

We use Doucouliagos (1995) to convert beta coefficients, such as 1, into partial regression coefficients. This technique offers an advantage over Hedges and Olkin's (1985) method of estimating effect magnitude using correlation coefficients. By converting the beta coefficients as partial regression coefficients, it is simple to compare beta coefficients at scale (PRC). Furthermore, PRC checks the misspecification bias in the model by investigating variations in estimating models and control variables (Hang et.al., 2018).

PRC is calculated with the t-value or p-value of the coefficient by this formula:

Partial correlation coefficient (PRC) = $\sqrt{\dfrac{(t-value)^2}{(t-value)^2+d}}$, Where d is the degrees of freedom and is equal to n-p-1 (n is a number of observations, p is the number of independent variables).

Additionally, we calculate standard error as:

Standard Error (s.e.) = $\sqrt{\dfrac{(1-PRC)^2}{d}}$

The calculation of the PRC or the effect size from all twelve trials allows for a comparison of the correlation between the two variables (underpricing and pre-issue analyst presence), as the correlation is determined while all other factors are held constant. After calculating the PRC or effect size for each of the twelve studies, we average them to produce the overall effect size, which we then estimate.

Using the random effect model, we estimate the combined effect size for twelve research. In meta-analysis, the random effect model corrects for sample size bias (or between-study variance) by providing weights that are adjusted for between-study variation in addition to within-study variation. As a result, all the weights assigned to the individual studies have been changed to account for any bias induced by differences in sample, in the fixed effect model; the research with the higher sample size will be given more weight and will differ considerably from the other small sample studies (Borenstein et al., 2010). However, under the random effect model, the weights will now be lowered downwards by the between-study variance component to balance the large sample study's overall dominance.

The random effect model estimates random fluctuations in each research to compute its comparative weight in relation to the other studies, as illustrated below:

$$w = \frac{1}{(SE_{r_{YX_k}} + \hat{v})}$$

Where, $\hat{v}$ is the random variation in the twelve studies and $SE_{r_{YX_k}}$ is the standard error of the Fisher Z-score of the effect size ($Z_{r_{YX_k}}$) of the individual studies, as shown below:

$$SE_{r_{YX_k}} = \frac{1}{(n-3)}$$

These effect sizes are transformed to Fisher-transformed z-score Standard error which calculated by this formula:

$$Z_{r_{YX_k}} = \frac{1}{2}\ln\left(\frac{1+r_{YX_k}}{1-r_{YX_k}}\right)$$

Table 1: Summary of Variables as Covariates in the Meta-regression

Variable	Working definition	Type	References
Industry	Industry dummy is used in the studies to control for the industry effects.	Binary: 1 if study controls for this variable, 0 otherwise	How and Low (1993)
Year	Year dummy is used in the studies to control for the year effects.	Binary: 1 if study controls for this variable, 0 otherwise	Tomzyck (1996)
Age	Age dummy is used in the studies to control for the age of the firm.	Binary: 1 if study controls for this variable, 0 otherwise	Jaitly (2004)
Underwriter's Reputation	Underwriter reputation dummy is used in the studies to control for the reputation effects.	Binary: 1 if study controls for this variable, 0 otherwise	Carter and Manaster (1990)
Assets	Asset dummy is used in the studies to control for the effects raised by assets of IPO firms.	Binary: 1 if study controls for this variable, 0 otherwise	Loughran and Ritter (2004)
Overhang	Overhang dummy is used in the studies to control for the effect created by ownership of the shares post-IPO by the owners (If they choose not to sell their stake on the listing day).	Binary: 1 if study controls for this variable, 0 otherwise	Bradley and Jordan (2002)
Venture Capitalist (VC)	VC dummy is used in the studies to control for the VC effects.	Binary: 1 if study controls for this variable, 0 otherwise	Barry et. al., (1990)
Country	Country dummy is used in the studies to control for the effects raised by US or the emerging market studies.	Binary: 1 if study controls for this variable, 0 otherwise	Chowdhry and Sherman (1996)

Note: This table contains a summary of the covariates used in the meta regression. The variables are all binary. Their citations are also provided in order to identify these variables from the current theory.

The factors mentioned in Table 1 are used as control variables in the meta-regression, and the average effect size is used as the dependent variable. The link between underpricing and pre-issue analyst presence is influenced by the control factors. As a result, it is recommended to do meta-regression using these control variables to identify the real influence of underlying research variables. Underwriter reputation, for example, is a control variable that influences underpricing on the listing day. As a result, we account for this variable to see if it has a moderating influence on the link between pre-issue analyst presence and underpricing.

Similarly, we account for factors such as industry, year, age, asset, overhang, and nation. As a control variable in the research under consideration, these variables are assigned the categorical values "0" for absence and "1" for presence (Klona, 2021). This is owing to a lack of continuous data for these variables in these twelve studies. For example, in most studies, the asset is indicated as a control variable, but its value is not clearly stated in the study articles. Similarly, overhang is assigned a value of "1" in meta regression as a covariate indicating the controlling impact of this variable in the twelve research, we selected for meta-analysis to determine whether it may alter pre-issue analyst presence to minimize underpricing.

4. Results and Discussion

4.1 Meta-analysis

Using a random effect model using data from 12 studies and 12 effect sizes and a total of close to 20,400 observations, the overall effect size is 4.9 percent and significant with a p-value of 0.017 (Table-2). The study's between-study variation is high, showing that factors have a moderating effect on the link between pre-issue analyst presence and underpricing. The heterogeneity test, which yields a Q-value of 95.437, further supports the moderating impact on the underpricing and analyst presence connection. This number indicates that the homogeneity null hypothesis is rejected. Furthermore, the p-value for the chi-squared test for homogeneity is 0.000, and the I-squared value is 88.5 percent (Table-2) suggesting heterogeneity, indicating that 88.5 percent of the observed variance in the studies is attributable to the variables in the studies.

Table 2: The Meta-Analysis Displaying the Impact Size Data for Twelve Individual Studies

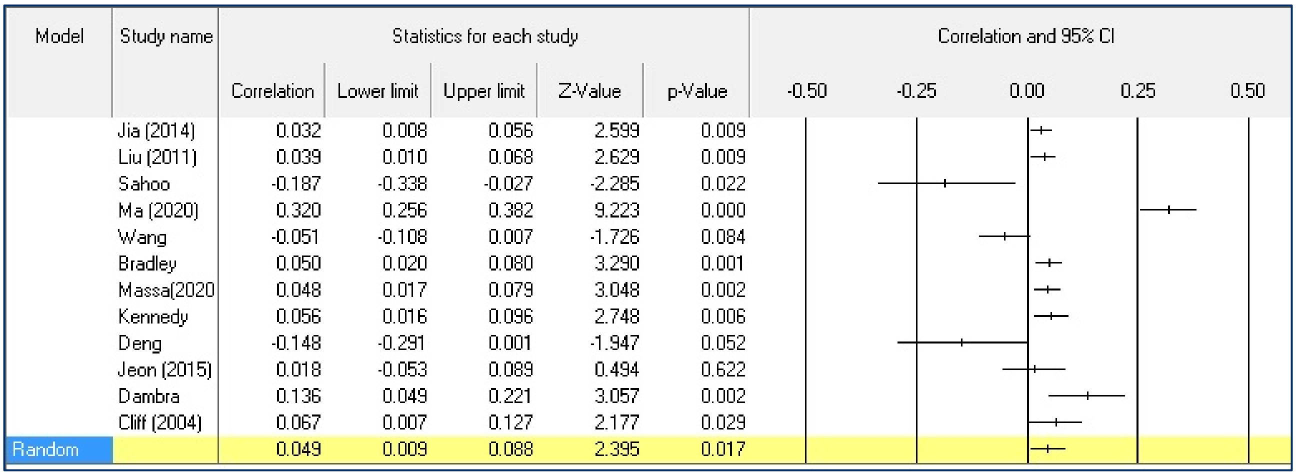
Study name	Sample size	Effect size	t-value	weight%
Cliff (2004)	1050	0.07*	2.18	8.70
Kennedy (2006)	2381	0.06**	2.75	9.81
Deng (2008)	194	0.15**	1.96	4.27
Wang (2008)	1168	0.05	1.728	8.85
Liu (2011)	4510	0.04**	2.63	10.28
Jia (2014)	1093	0.03**	2.6	10.46
Sahoo (2014)	157	0.19**	2.306	3.88
Bradley (2015)	4180	0.05***	3.292	10.26
Jeon (2015)	631	0.02	0.494	8.06
Dambra (2018)	363	0.14**	3.07	7.12
Massa(2020)	3949	0.05**	3.05	10.21
Ma (2020)	781	0.32***	9.4	8.11
I-V pooled ES		0.049**	2.39	100.00
Heterogeneity Chi-squared = 95.47			(df=11, p-value= 0)	
I-squared = 88.5% (variations due to heterogeneity)				

Note: This table shows the effect size data of all the twelve studies. The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

As the data demonstrate, pre-issue analyst presence enhances underpricing of IPOs. This conclusion is consistent with Deng and Dorfleitner's (2008) and He and Lin's (2015) findings, which support the concept of greater first-day returns due to analysts' pre-issue presence. The cause for this outcome might be attributed to the issue's co-biased manager's recommendation to the purchase side, or to the analysts present in the underwriter's syndicate (Loughran and Ritter, 2004). This skewed information produces information asymmetry, which results in greater early returns for the share due to its larger demand bias.

Figure 1 illustrates the contribution of each research to the overall conclusion using a forest plot. The size of the sample is shown by the black vertical line in the forest plot for each research, and the confidence interval is indicated by the horizontal line. The vertical line at the bottom of the picture depicts the overall effect size and its importance since it intersects the interval's midpoint. This discovery is connected to the considerable influence of analyst presence before to issuance on underpricing. The total confidence interval of the effect magnitude is shown by the length horizontal line.

Figure1: Forest Plot



Model	Study name	Statistics for each study				
		Correlation	Lower limit	Upper limit	Z-Value	p-Value
	Jia (2014)	0.032	0.008	0.056	2.599	0.009
	Liu (2011)	0.039	0.010	0.068	2.629	0.009
	Sahoo	-0.187	-0.338	-0.027	-2.285	0.022
	Ma (2020)	0.320	0.256	0.382	9.223	0.000
	Wang	-0.051	-0.108	0.007	-1.726	0.084
	Bradley	0.050	0.020	0.080	3.290	0.001
	Massa(2020	0.048	0.017	0.079	3.048	0.002
	Kennedy	0.056	0.016	0.096	2.748	0.006
	Deng	-0.148	-0.291	0.001	-1.947	0.052
	Jeon (2015)	0.018	-0.053	0.089	0.494	0.622
	Dambra	0.136	0.049	0.221	3.057	0.002
	Cliff (2004)	0.067	0.007	0.127	2.177	0.029
Random		0.049	0.009	0.088	2.395	0.017

Note: This figure depicts the contribution of each study to the calculation of the cumulative effect size. Horizontal line shows the confidence interval and vertical small line shows effect size of the study.

The vertical line at the bottom of the picture depicts the overall effect size and its importance since it intersects the interval's midpoint. This discovery is connected to the considerable influence of analyst presence before to issuance on underpricing. The total confidence interval of the effect magnitude is shown by the length horizontal line. The total impact size of analyst presence on underpricing is positive and significant in the US sample of research, at 1%.

Table-3 shows that the effect magnitude is given as 5%. The impact size in the developing market sample is smaller, at 1.3 percent, and negligible (see Table-4). This conclusion is intriguing, and one of the explanations might be the homogeneity of the US study population. The reported I-squared for US studies is low (0.04%, Table-3), indicating that the observed variance in US studies is not related to between-study variation. The observed variance in emerging market research, however, is due to between-study variation, since I-squared is 97.59 percent, showing significant heterogeneity in emerging market studies. This explains the insignificance of the impact size in developing market research

Table 3: Meta-Analysis Results Showing the Effect Size Data for Six US IPO Studies

Study name	Sample size	Effect size	t-value	weight%
Liu (2011)	4510	0.039**	2.63	33.35
Bradley (2015)	4180	0.05***	3.292	31.83
Kennedy (2006)	2381	0.056**	2.75	17.72
Jeon (2015)	631	0.018	0.494	5.52
Dambra (2018)	363	0.136***	3.07	3.80
Cliff (2004)	1050	0.067	2.18	7.79
I-V pooled ES		0.050***		100.00
I-squared = 0.04%				

Note: This table shows the effect size data of six non-US studies. The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Table 4: Meta-Analysis Results Showing the Effect Size Data for Six US IPO Studies

Study name	Sample size	Effect size	t-value	weight%
Jia (2014)	1093	0.032	2.6	18.02
Sahoo (2014)	157	-0.187	2.306	14.38
Ma (2020)	781	0.320	9.4	17.39
Wang (2008)	1168	-0.050	1.728	17.51
Massa(2020)	3949	0.048	3.05	17.95
Deng (2008)	194	-0.148	1.96	14.75
I-V pooled ES		0.013***		100.00
I-squared = 0.04%				

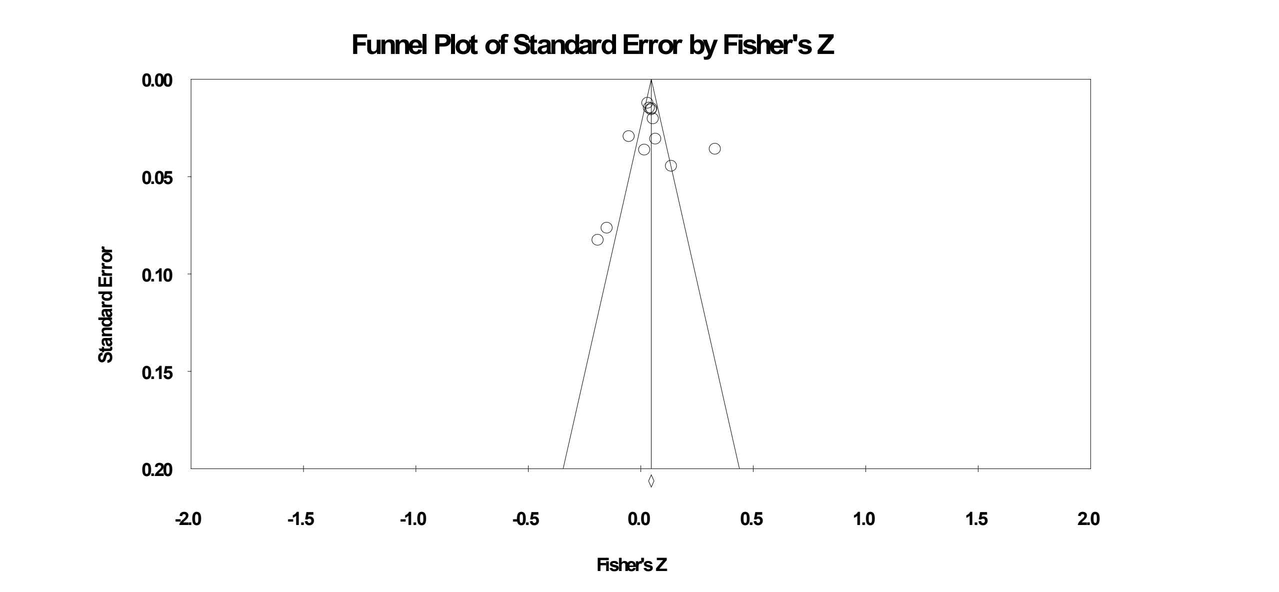
Note: Table shows the effect size data of six US studies. The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

The disparity in outcomes between US and developing market research can be ascribed to below mentioned factor. The developed markets, for example, have established companies with a defined capital structure. As a result, the underwriter or book manager may properly evaluate the issuing business and establish the offer price to attract the appropriate attention from stock analysts and prospective investors following the IPO.

In contrast, in emerging market firms, the capital structure is less effective and the determinants of it are not precisely known, making them slightly riskier to value (Eldomiaty, 2008), making it difficult for the underwriter or book manager to estimate the intrinsic value of the firm's IPO and thus the offer price. In this instance, high-risk businesses may engage reputed underwriters, resulting in a larger pre-issue analyst presence, which decreases underpricing (Bowen et al, 2008).

Figure 2 depicts a funnel plot used to determine the presence of publication bias in a meta-analysis. This figure identifies the bias in the meta-analysis caused by unpublished studies with negligible p-values (Harbord et al, 2006). The standard error is represented on the y axis of the funnel plot in Figure-2, and the effect size estimate is shown on the x axis of each study. The figure clearly shows that the studies with the highest weight converge to the pooled estimate, which is at the top of the curve. Nonetheless, three investigations are located outside the plot's left boundary. They are, nevertheless, far closer to the confidence limits. One research is outside the funnel plot's right bounds and also farther away from it. This demonstrates the presence of publication bias in these four papers, and we used the small study bias test to validate it.

Figure 2: Funnel Plot



Note: This is a plot of standard error vs Fisher's z-score. Studies that are outside of the left and right margins add to the publication bias.

The small study bias test illustrates the variation in findings between small and big studies owing to differences in research quality. Egger's test (Egger et al., 1997) was employed for this (see Table-5). The null hypothesis states that no small study bias exists. The two-tailed p-value is 0.96, and we are unable to reject the null hypothesis, indicating that this study is free of small study bias. As a result, despite the evidence of publication bias in four studies in our study, Egger's test revealed that the divergence of four studies from the confidence limits is attributable to other reasons.

Table 5: Egger's Test for the Identification of Small Study Bias

Intercept	0.07805
standard error	1.884
t-value	0.04
degree of freedom	10
p-value	0.96

4.2 Meta-regression

Meta-regression is carried out with study-specific characteristics serving as control variables (see Table-1) and the cumulative effect size of twelve studies serving as the dependent variable. We computed the Hausman's test in all three models, model-1, model-2, and model-3, to check for any confounding effect or enodogeneity in the regression model (see Table-6).

Table-6 Meta regression results for three models

To estimate the coefficients in the Meta regression, the random effect (RE) model is employed. Meta regression is carried out with the dependent variable being effect size and the independent variables being study level characteristics. All the explanatory variables in the research are binary, with values 1 and 0 indicating their existence or absence. The symbols *, **, and *** in the table denote significance levels of 10%, 5%, and 1%, respectively.

Variable	Model-1	Model-2	Model-3
Intercept	-0.25***	-0.23**	-0.24**
Industry	-0.19*	-0.21*	-0.21*
Year	0.3***	0.29***	0.29***
Age	0.14*	0.12	0.12
Underwriter reputation	0.12**	0.13**	0.12**
Asset		0.03	0.02
Overhang	0.11	0.09	0.1
VC			0.02
Country	0.09	0.08	0.09
N	**12**	**12**	**12**
Hausman's test p-value	**0.59**	**0.68**	**0.77**
Model	**RE**	**RE**	**RE**
Adj R^2	**0.64**	**0.65**	**0.66**
Model validity	**Yes, at p-value= 0.02**	**Yes, at p-value=0.03**	**Yes, at p-value=0.04**
Goodness of fit	**Yes, at p-value= 0.000**	**Yes, at p-value=0.000**	**Yes, at p-value=0.000**

We test the null hypothesis that there is no systematic difference between the Fixed and Random effect model coefficients. We fail to reject the null hypothesis since the estimated p-value is 0.59 for model-1, 0.68 for model-2 and 0.77 for model-3. This demonstrates the lack of endogeneity in the three models we estimate. As a result, we employ the random effects model to estimate the coefficients in the three models.

Table-6 shows the estimates of the coefficients by applying the random effects model. Year, industry, and underwriter repute are all significant variables in all the model specifications, i.e., model-1, model-2, and model-3. When all variables, except asset and VC, are included in the model, the underwriter's reputation is significant at the 5% level of significance.

The industry and year fixed effects covariate are both significant. As a result, the industry and year variables in the research are sources of heterogeneity and moderate the relationship between pre-issue analyst presence and IPO underpricing. The negative sign of the coefficient of the industry variable indicates that when the research study controls for industry fixed effects, the impact of analysts' presence prior to the IPO on underpricing is reduced. The reduction in effect size as a result of industry effect as a control variable demonstrates that it can lead to improved efficiency in information transmission since it adjusts for price clustering in the given industry (Cao and Shi, 2006) and therefore lowers underpricing.

In research that adjusts for years fixed effects in the regression model, the effect magnitude is greater. Underpricing is a transient phenomenon that is highly dependent on market conditions. Increased effect size in research controlling for year fixed effects shows that in a short period of time, ignoring external economic fixed effects, pre-issue analyst coverage has the tendency to distort the pricing of the IPO. Significance of underwriter reputation, with a p-value of 0.0396 and a positive effect size of 0.12, demonstrates that underwriter reputation increases the influence of pre-issue analyst presence on IPO underpricing. These findings are consistent with those of Beatty and Welch (1996) and Loughran and Ritter (2004), who showed a positive correlation between underwriter reputation and IPO underpricing. To comprehend the beneficial impact of underwriter reputation on effect size, we must first appreciate the link between underwriter reputation and IPO analysts.

Reputable underwriters attract analysts to follow the firm's IPO, and analysts begin making recommendations prior to the IPO listing day; the observation that the underwriter's reputation has a beneficial influence on the effect size shows the issue's enthusiasm among investors. This generates excitement for the IPO among investors, who are drawn to the issue in order to raise its subscription. On the day of the listing, pay-off to the initial investors in the business is consistent to the spinning hypothesis (Loughran and Ritter, 2004). Furthermore, the issuer's willingness to leave money on the table is related to confirming long-term investor relationships as well as success in attracting uninformed investors (Beatty, 1986).

6. Conclusion

The meta-analysis of the twelve studies has assisted in identifying the aggregate effect of pre-issue analyst presence and its role in IPO underpricing. The link between them is ambiguous in the literature. The meta-analysis reveals that the total effect size of the twelve studies is substantial and favourable. The extent of the favourable effect implies that IPO underpricing has increased as a result of pre-IPO analyst presence. As a result, rather than creating a more efficient information environment for investors, the presence of analysts prior to the IPO causes an information gap, resulting in over-hyping of the issue and higher initial returns on the first day of issue. This finding is also consistent with the spinning hypothesis, which promotes underpricing as a method of rewarding venture capitalists or other early investors and advocates for the inclusion of reputable underwriters in the IPO process.

Furthermore, statistics from US IPOs suggest that analyst presence has a significant impact on IPO underpricing. Due to the variability in their research, the impact size of the connection between analyst presence covering the business and underpricing in emerging market's IPOs is smaller but not negligible. The homogeneity of research in the United States and the heterogeneity of the developing market sample is attributed to this result. The reason for the disparity in their conclusions is due to differences between researchers, which may be related to the difficulty that IPO analysts or issue underwriters may have while valuing the business. As a result of their varying levels of capital market maturity, emerging market businesses exhibit heterogeneity in their outcomes. As a result, this study is effective in isolating the influence of nation as a covariate.

Moreover, the reputation of the underwriters amplifies the effect of analyst presence on IPO underpricing. The underwriter's reputation has an overall favourable and substantial influence on the link between analyst coverage and IPO underpricing, according to the moderation analysis of the variables on effect size. As a consequence, reputable underwriters have demonstrated the impact of analysts' presence prior to the underpricing of the IPO. As a result, the finding validates the information asymmetry theory for the issuing business, which depicts the IPO underpricing as a result of price manipulation by the underwriter and its syndicate, which includes analysts. More research is needed to understand the factors that contribute to the link between pre-issue analyst presence and underpricing.

References

Aggarwal, R. K., Krigman, L., & Womack, K. L. (2002). Strategic IPO underpricing, information momentum, and lockup expiration selling. Journal of Financial Economics, 66(1), 105–137.

Alanazi, A. S., & Al-Zoubi, H. A. (2015). Extreme IPO underpricing and the legal environment in wealthy emerging economies. Journal of Multinational Financial Management, 31, 83–103.

Ap Gwilym, O., & Verousis, T. (2010). Price clustering and underpricing in the IPO aftermarket. International Review of Financial Analysis, 19(2), 89–97.

Arnold, T., Fishe, R. P. H., & North, D. (2010). The Effects of Ambiguous Information on Initial and Subsequent IPO Returns. Financial Management, 39(4), 1497–1519.

Baron, D. P. (1982). A Model of the Demand for Investment Banking Advising and Distribution Services for New Issues. The Journal of Finance, 37(4), 955.

Barry, C. B., Muscarella, C. J., Peavy, J. W., & Vetsuypens, M. R. (1990). The role of venture capital in the creation of public companies. Journal of Financial Economics, 27(2), 447–471.

Bear, R. M., & Curley, A. J. (1975). Unseasoned Equity Financing. The Journal of Financial and Quantitative Analysis, 10(2), 311.

Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. Journal of Financial Economics, 15(1-2), 213–232.

Beatty, R. P., & Welch, I. (1996). Issuer Expenses and Legal Liability in Initial Public Offerings. The Journal of Law and Economics, 39(2), 545–602.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. Journal of Financial Economics, 24(2), 343–361.

Boulton, T.J., Smart, S.B. & Zutter, C.J. (2020). Worldwide short selling regulations and IPO underpricing. Journal of Corporate Finance, 62, 101596.

Bouzouita, N., Gajewski, J.-F., & Gresse, C. (2015). Liquidity Benefits from IPO Underpricing: Ownership Dispersion or Information Effect. Financial Management, 44(4), 785–810.

Bowen, R. M., Chen, X., & Cheng, Q. (2008). Analyst Coverage and the Cost of Raising Equity Capital: Evidence from Underpricing of Seasoned Equity Offerings. Contemporary Accounting Research, 25(3), 657–700.

Bradley, D. J., & Jordan, B. D. (2002). Partial Adjustment to Public Information and IPO Underpricing. The Journal of Financial and Quantitative Analysis, 37(4), 595.

Bradley, D., Kim, I., & Krigman, L. (2015). Top VC IPO underpricing. Journal of Corporate Finance, 31, 186–202.

Carter, R., & Manaster, S. (1990). Initial Public Offerings and Underwriter Reputation. The Journal of Finance, 45(4), 1045.

Chang, C., Chiang, Y.-M., Qian, Y., & Ritter, J. R. (2016). Pre-market Trading and IPO Pricing. The Review of Financial Studies, 30(3), 835–865.Chourou, L., Saadi, S., & Zhu, H. (2018). How does national culture influence IPO underpricing? Pacific-Basin Finance Journal, 51, 318–341.

Chowdhry, B., & Sherman, A. (1996). International differences in oversubscription and underpricing of IPOs. Journal of Corporate Finance, 2(4), 359–381.

Cooper, H. M. (1982). Scientific Guidelines for Conducting Integrative Research Reviews. Review of Educational Research, 52(2), 291–302.

Daily, C. M., Trevis Certo, S., Dalton, D. R., & Roengpitya, R. (2008). IPO Underpricing: A Meta-Analysis and Research Synthesis. Entrepreneurship Theory and Practice, 27(3), 271–295.

Dambra, M., Field, L. C., Gustafson, M. T., & Pisciotta, K. (2018). The consequences to analyst involvement in the IPO process: Evidence surrounding the JOBS Act. Journal of Accounting and Economics, 65(2-3), 302–330.

Degeorge, F., Derrien, F., & Womack, K. L. (2007). Analyst Hype in IPOs: Explaining the Popularity of Bookbuilding. Review of Financial Studies, 20(4), 1021–1058.

Deng, H., & Dorfleitner, G. (2008). Underpricing in Chinese IPOs–some recent evidence. Applied Financial Economics, 18(1), 9–22.

Dimovski, W., Philavanh, S., & Brooks, R. (2010). Underwriter reputation and underpricing: evidence from the Australian IPO market. Review of Quantitative Finance and Accounting, 37(4), 409–426.

Doucouliagos, C. (1995). Worker Presence and Productivity in Labor-Managed and Participatory Capitalist Firms: A Meta-Analysis. ILR Review, 49(1), 58–77.

Eldomiaty, T. I., & Azim, M. H. (2008). The dynamics of capital structure and heterogeneous systematic risk classes in Egypt. International Journal of Emerging Markets, 3(1), 7–37.

Fullbrunn, S., Neugebauer, T. & Nicklisch, A. (2019). Underpricing of initial public oferings in experimental asset markets. Experimental Economics, 23, 1002–1029.

Glass, G. V. (1976). Primary, Secondary, and Meta-Analysis of Research. Educational Researcher, 5(10), 3.

Hang, M., Geyer-Klingeberg, J., Rathgeber, A. W., & Stöckl, S. (2018). Measurement matters—A meta-study of the determinants of corporate capital structure. The Quarterly Review of Economics and Finance, 68, 211–225.

Harbord, R. M., Egger, M., & Sterne, J. A. C. (2006). A modified test for small-study effects in meta-analyses of controlled trials with binary endpoints. Statistics in Medicine, 25(20), 3443–3457.

He, H., & Lin, Z. (2015). Analyst Following, Information Environment and Value Relevance of Comprehensive Income: Evidence from China. Asia-Pacific Journal of Financial Studies, 44(5), 688–720.

Hedges, L. V., & Olkin, I. (1985). Statistical methods for meta-analysis, Elsevier.

How, J. C. Y., & Low, J. G. (1993). Fractional ownership and underpricing: signals of IPO firm value? Pacific-Basin Finance Journal, 1(1), 47–65.

Hu, W.Y. & Ritter, J. (2007). Multiple Bookrunners in IPOs. SSRN electronic journal.

Hunter, John E., & Schmidt, Frank L. (1990). Methods of Meta-Analysis: Correcting Error and Bias in Research Findings. Newbury Park, CA: Sage, 592 pages.

Jaitly, S. (2004). Pricing of IPOs and their after issue performance in the Indian equity market. Managerial Finance, 30(1), 29–45.

Jeon, J. Q., Lee, C., Nasser, T., & Via, M. T. (2015). Multiple lead underwriter IPOs and firm visibility. Journal of Corporate Finance, 32, 128–149.

Jia, C., Ritter, J. R., Xie, Z., & Zhang, D. (2018). Pre-IPO Analyst Coverage: Hype or Information Production? SSRN Electronic Journal.

Jia, C., Ritter, J. R., Xie, Z., & Zhang, D. (2014). Analyst Coverage in the pre-markets of IPOs. SSRN Electronic Journal.

Kennedy, D. B., Sivakumar, R., & Vetzal, K. R. (2006). The implications of IPO underpricing for the firm and insiders: Tests of asymmetric information theories. Journal of Empirical Finance, 13(1), 49–78.

Klona, M. (2021). The Days After COVID-19: A Meta-Analysis on the Impact of Epidemics and Pandemics on Long-Term Macro-Economic Performance. American Business Review, 24(1), pp-187-224.

Lin, H., & McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics, 25(1), 101–127.

Liu, X., & Ritter, J. R. (2010). The Economic Consequences of IPO Spinning. Review of Financial Studies, 23(5), 2024–2059.

Liu, X., & Ritter, J. R. (2011). Local underwriter oligopolies and IPO underpricing. Journal of Financial Economics, 102(3), 579–601.

Loughran, T. & Ritter, J. (2004). Why Has IPO Underpricing Changed Over Time? Financial Management, 33 (3), 5-37.

Massa, M., & Zhang, L. (2020). Local investor horizon clientele and IPO underpricing. Journal of Financial Markets, 100587.

McDonald, J. G., & Fisher, A. K. (1972). NEW-ISSUE STOCK PRICE BEHAVIOR. The Journal of Finance, 27(1), 97–102.

Michaely, R., & Womack, K. L. (1999). Conflict of Interest and the Credibility of Underwriter Analyst Recommendations. Review of Financial Studies, 12(4), 653–686.

Muscarella, C. J., & Vetsuypens, M. R. (1989). A simple test of Baron's model of IPO underpricing. Journal of Financial Economics, 24(1), 125–135.

Rajan, R., & Servaes, H. (1997). Analyst Following of Initial Public Offerings. The Journal of Finance, 52(2), 507.

Reilly, F.K. and Hatfield, K. (1969). Investor Experience with New Stock Issues. Financial Analyst Journal, Vol. 25, No. 5 (Sep. - Oct. 1969), pp. 73-80.

Roulstone, D. T., & Chicago, U. of. (2003). Analyst Following and Market Liquidity. Contemporary Accounting Research, 20(3), 552–578.

Sahoo, S. (2014). Do analyst's pre-issue recommendation create value? Empirical evidence from Indian IPO market. The Spanish Review of Financial Economics, 12(2), 82–95.

Sterne, J. A., & Egger, M. (2001). Funnel plots for detecting bias in meta-analysis. Journal of Clinical Epidemiology, 54(10), 1046–1055.

Tomczyk, S. (1996). Auditor reputation and initial public offerings by foreign companies. Journal of International Accounting, Auditing and Taxation, 5(2), 249–262.

Wang, K. (2008). Does pre-deal research reduce IPO underpricing? Pacific Accounting Review, 20(3), 234–253.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

THE DAVIDS AND THE GOLIATHS: INVESTMENT DYNAMICS AND PERFORMANCE DIFFERENTIALS OF SMALL FIRMS AND FAMILY-CONTROLLED LARGE FIRMS IN FOUR SECTORS OF THE INDIAN MARKET

Jaideep Ghosh[1]

1. School of Management and Entrepreneurship, Shiv Nadar University, India

* Corresponding Author: Jaideep Ghosh, Shiv Nadar University, India, ✉ Email: jghosh20770@gmail.com

Abstract

This study explores investment dynamics based on interlocking directorates and performance differentials of two kinds of publically traded firms operating in the Indian market: Non-affiliated, small firms and family-controlled, large firms. Considering four important sectors (fashion; manufacturing; transport; food) of the Indian market, this study finds that a significant fraction of the small firms are able to maintain stable performance over time by forging strategic ties with similar other firms in transactional supply-chain modes, although many large, family-controlled firms dominate sections of the market. Firm board interlocks play a crucial role in strategizing investment decisions and tie-forging processes for the small firms. This study contributes to a deeper understanding of the question concerning how investments of small firms might be governed through interfirm ties of coordinated and cooperative activities. The results have important implications for small firms operating in the markets of a number of emerging economies of the world.

Keywords: Firm investment structures; Non-affiliated, small firms; Family-controlled, large firms; Firm performance; Firm board interlocks

1. Introduction

A question of major theoretical and empirical interest concerns how capital investment structures of small-sized[1], non-affiliated[2] (SNA) firms enable them to compete in a market, significant sections of which are dominated by large, family-controlled (LFC) firms[3]. Earlier scholars have investigated various aspects of this question (Carney, 2005; Claessens & Fan, 2002; Daily & Dollinger, 1992; Klapper & Love, 2004; La Porta et al., 1999; Miller et al., 2008; Randolph et al., 2021), which have important implications for many emerging economies. In this paper, we examine this question by closely looking at the dynamics of investments and performances of these firms over time. We test our model using empirical data from four important sections of the Indian industry: fashion; manufacturing; transport; and food.

---

[1] We only investigate stock-listed companies. Firms are considered "small" if they are much smaller than "large" firms in terms of their total asset holdings, total sales, market values of equity, and the number of employees.

[2] In this paper, "non-affiliated" refers to firms that are not controlled by any business families.

[3] A few of these firms are even multinationals, which are commonly called emerging economy multinational enterprises (EEMNEs)

With large concentrations of a family's wealth in a group of LFCs, the family promoters, by dint of their substantial ownership stakes and influential positions on the firm boards, dictate major governance policies for the firms under their direct leadership, which are motivated primarily by their personal attitudes, ideas, objectives, policies, and politics. Over the years, this phenomenon has come to govern the dynamics of the Indian market in multiple sectors of the industry (Chakrabarti et al., 2008; Gollakota & Gupta, 2006; Khanna & Rivkin, 2001; Ray et al., 2018; Selarka, 2005). Importantly, LFCs are not always single-family concerns where ownership and control are limited to single-family units (Litz, 1995). These Goliaths of the industry could even be controlled by the immediate and extended members of influential business families, with first cousins, second cousins, in-laws, parents, grandparents, uncles, aunts, and possibly many other relations of blood or marriage serving as promoters or outside directors on the firm boards (Jackling & Johl, 2009; Khanna & Palepu, 2000; Westhead et al., 2001).

Since colonial times and even after India's independence in 1947, these LFCs, with their select and influential (and sometimes politically powerful!) coterie of family members, community stalwarts, and political advisors have controlled large sections of the Indian market (Bajpai, 2016; Gollakota & Gupta, 2006; Kumar & Singh, 2013). These firms – the Goliaths of the industry – vary in size and age, as well as in their degree of diversification, but in time, their influence spreads across sectors to dominate the market that includes other players, such as the Davids of the industry – the SNAs (Manos et al., 2007; Zahra & Pearce, 1989).

Some recent work notwithstanding, this critical issue has remained somewhat underrepresented in the extant literature on many emerging economies. The present study does not claim to present a theoretical model to explain the issue in all facets of it. Rather, the study is exploratory in nature. In particular, it makes evaluative analyses of the investment and performance differentials of SNAs in comparison with those of LFCs operating in the Indian market. Specifically, it contributes to this literature in two ways. First, it finds that, although SNAs continuously contend with the powerful spatiotemporal advantage enjoyed by influential LFCs, many SNAs do perform consistently well. These firms are empowered by large-scale, open-market conditions in the Indian market today, along with opportunities for global business transactions, internationalization, and improved corporate governance policies instituted by market regulators in recent years. Second, the study explores conditions under which SNAs are able to withstand the dominant competitive pressure of LFCs by strategically leveraging board-interlocked resources in proliferating transactional relationships with allied firms not only in the same industry sector but also across different ones. To be effective, the firms make carefully chosen, judiciously planned, and purposeful investments in capital expenditures to enhance their internal efficiency as well as to make their interfirm business operations more productive, smooth, and profitable. They develop, in this way, a select coterie of firms in order to be able to compete in the market, which critically determines their future survival and growth[4]. This strategy constitutes the bedrock of their competitive advantage and business support.

[4] Indian LFCs also participate in supply-chain networks (Bajpai, 2016). However, because they are strongly family-controlled, a large number of family members or extended relations of promoters sit on their boards as outside directors, simply supporting all decisions taken by the promoters. The non-functional, decorative role of these directors does not help in making networking connections for strategic investments for the company (Gollakota & Gupta, 2006). Therefore, although LFCs engage in interlocking directorates and collaborative activities, the large family dominance of their boards makes them much less efficient than SNAs in terms of reducing risks and increasing chances of success by making strategic decisions for networked investments (Kumar & Singh, 2013).

2. Capital Investments

2.1 Theoretical considerations

Primarily, firms engage in two modes of investments. First, for running core operations utilizing labor, infrastructure, technology, plants, machinery, other equipment, and so on, essential investments vary from one firm to another and depend on the internal requirements of a firm in diverse channels of its business operations (Almeida & Campello, 2007; Booth et al., 2001; Short, 1994). Second, the investment structures for interfirm supply-chain networked transactions transcend the specifics of any particular firm (Baiman & Rajan, 2002; Paulraj et al., 2008; Rungtusanatham et al., 2003). These latter types of investments are coordinated with allied investments of firms' supply-chain partners and are needed to reduce interfirm transactional non-uniformities. The capital investment objective is to not only enhance the firm's internal performance but also to ensure transactional smoothness across the chain of firms brought together through their focused, interlinked operations (Bidault & Salgado, 2001; Huggins, 2010; Kapoor, 2014; Parmigiani & Mitchell, 2009). A principal mechanism by which the supply-chain partnering process is facilitated lies in board interlocks of firms, in which independent directors are selected on the firm board from its partner firms and in the degree to which resources brought into the firm by these directors can be effectively leveraged (Ingley et al., 2017).

For firms to effectively perform their business operations in supply-chain modes, investments in asset procurement and utilization are necessary to meet the demands of their supported operations (Cousins & Menguc, 2006; Thomas & Griffin, 1996). Enhanced investment coordination with partners serves to maximize future cash flows as well as to reduce short-term oscillations and volatilities in production and support functions (Baiman & Rajan, 2002; Craighead et al., 2007). In a growth-driven mode, a firm's supplier-base expands over time, in response to which well-directed investments are made by firms to cope with rising demands for increasing inventory turnover, stocking facilities, trade receivables, and other asset forms (Bidault & Salgado, 2001; Lee et al., 1997). Further investments must also be made to enlarge relevant distribution channels of the consumer-base to meet specific requirements for cash flows and material resources. These investments must be directed to ensure that transactions down the supply chain are largely free from undesirable oscillations (Thomas & Griffin, 1996).

In order to establish a balance, interfirm operations must be reconciled with those that are needed for internal production effectiveness and efficiency. The investments depend on a number of factors, including, for instance, firm age, size, and industry; equity and debt positions; number and skill-levels of employees; current capacity utilization; and so on (Almeida & Campello, 2007). Whereas interlinked investments benefit from interfirm knowledge and resources, firm-specific investments depend on a firm's internal capacities and requirements for knowledge and resources and do not require external input in order to be functional (Nise, 2015). However, in making strategic investment decisions, there frequently arises a tension between these investment modes. Nevertheless, a balance may eventually emerge. If it does, then levels of internal investments can be reconciled with degrees of interfirm investments under prevailing market conditions. The balance ensures a uniformity between the investment modes and enhance financial performance over time.

2.2 Firm Connectivity Structure

A large fraction of SNAs in India capitalizes on strategic investments by means of transaction-linked relationships with similar other firms in order to find expanding opportunities (Gollakota & Gupta, 2006; Goswami, 2002; Sankar et al., 2015). Prior research has also shown that small firms benefit from strategic investments in order contend with market dominance exercised by large firms by virtue of their size, financial strength, and marketing power (Young et al., 2014). In this regard, resource dependence theory underscores the critical resource provision role played by the firm board (Hillman & Dalziel, 2003). Board directors facilitate the creation of relationships with an organization's external environment (Pfeffer & Salancik, 1978), serve as channels between the organization and its investors

(McDonald et al., 2008), and help company executives identify potential growth linkages through financial ties that include infrastructure setup, internal loans, and debt opportunities (Bandyopadhyay & Das, 2005; Manos et al., 2007). The diversity in the board provides the necessary conduit for expanding firm operations in multiple directions (Ingley et al., 2017)[5].

Specifically, when SNAs operate in an industry that is vastly dominated by a number of influential LFCs, it is strategically advantageous for them to maintain a partnering network with similar firms on its supply-chains in different sectors. Most frequently, these connections materialize through the sharing of common board directors (Bengtsson & Kock, 1999; Elango & Pattnaik, 2007). Over time, a mature relationship governs the current and future capital structures of firms, influencing the existing patterns of firm-interlinked investments. Afterwards, as connections consolidate and become sufficiently stable, they constitute a support system for capital structures (Booth et al., 2001; Simpson & Gleason, 1999).

Although a number of influential LFCs[6] in India also tap opportunities for similar investments through their interlocking directorates, these are frequently limited to the firms that they currently control or those that they are in the process of acquiring in course of their business expansions. The strategic decisions are governed primarily by the influence of the family-related promoters sitting on firm boards (Khanna & Palepu, 2000; Randolph et al., 2021; Zahra & Pearce, 1989). Oftentimes, a one-sided family diktat dominating such critical investment decisions causes a failure for the vast majority of LFC firms to attain the desired investment balance. By contrast, the balance emerges for SNAs through the strategic deployment of their interlocking ties, even when influential family connections or strong community relationships do not exist.

3. Framework for Exploratory Analysis

3.1 Firm Interlock Network

Our model is conceptualized with capital investments of firms unfolding on a network comprising n firms that are connected by ties of interlocking directorate through the sharing of one or more directors on the boards[7]. A tie carries a weight proportional to the total number of *shared* directors on the boards. Such a network of size n with m ties can be characterized by an n-dimensional, square, symmetric *weight* matrix $\boldsymbol{W}$: $W_{ij} = W_{ji} = 1, 2, \ldots,$ if firms i and j are associated by sharing a number $1, 2, \ldots$ of directors; $W_{ij} = 0$ otherwise. Conceptually, when two firms share many directors on their boards, their coupling strength is large compared with when they shared only a few directors. A strong sharing offers a greater opportunity for coordinated and strategic decision-making. However, a tie's directionality is irrelevant.

3.2 Conditions for Firm Investment Behavior

Three conditions govern firm investment behavior:

---

[5] Interlocking directorates are well-known for the management of cooperation. However, it is by no means the *only* possible instrument to manage cooperation and network ties for investment purposes. Nevertheless, for most firms in India, board interlocks play the most significant role in networking activities and decision-making (Bajpai, 2016).

[6] Some of these firms are even members of major business groups controlled by families of industrialists or mercantile communities in the country.

[7] For the present purpose, a firm and its board are largely synonymous.

1. Each firm exhibits a characteristic form for the firm-specific investment.
2. Firm-specific investments are distinct from firm-interlinked investments.
3. Investment balance attains over a period when transients are smoothed out or eliminated.

Condition 1 approximates the effect that financial decisions affect each firm in a similar way in the absence of rare events, market instabilities, or turbulences. This signifies that the firm-specific investment function exhibits *behavioral isomorphism*. Condition 2 prohibits interactive effects to operate between the two forms of investments over the period of interest. Condition 3, which is common in most financial and macroeconomic studies, implies that the transaction-linked ties between firms take some appropriate time to consolidate, whenever they do.

3.3 Investment Dynamics on Board Interlock Network

The investment variable $I_i(t)$ represents the amount of capital expenditures made by firm i. A knowledge of this variable for all the firms in the network characterizes an investment state for the entire system. This quantity is shaped board interlock networks of firms, because, as already explained before, firm investment dynamics is largely dependent on-board structures. It is therefore possible to represent a specific investment configuration at time t by the n-dimensional vector $\vec{I}(t) = \{I_1(t), I_2(t), \dots, I_n(t)\}$, where the index $i = 1,2, \dots, n$ runs over all firms in the network (Barrat et al., 2008; Newman, 2010).

The rate of change of $I_i(t)$ for firm i is envisaged as a superposition of two *independent* investment modes: (1) firm-specific, characterized by the function $\psi_i(I_i)$ pertaining to firm i's unique, internal investment; (2) firm-interlinked, characterized by the function $\chi(\boldsymbol{W}, I)$ pertaining to firm i's investment in coordination with its supply-chain partners. The complete dynamics, then, assumes the form: $\dot{I}_i = \psi_i(I_i) + \chi(W_{ij}, I_i)$, where the overdot represents time derivative. The $\chi(W, I)$ term embodies linearly additive terms in the investment: $\chi(W_{ij}, I_i) = \sum_j W_{ij}\varphi(I_i, I_j)$, where $\varphi(I_i, I_j)$ is a 2-firm, dyadic function coupling the investments of firms i and j. To make the framework general, we take $\varphi(I_i, I_j)$ to be *non-symmetric*: $\varphi(I_i, I_j) \neq \varphi(I_j, I_i)$. Additionally, by the assumption of behavioral isomorphism, we set $\psi_i(I_i) = \psi(I_i), \forall\, i = 1, \dots, n$. The complete investment dynamics now takes on a simpler appearance: $\dot{I}_i = \psi(I_i) + \sum_j W_{ij}\varphi(I_i, I_j)$.

3.4 Investment Balance

In the interfirm mode, a *deficit* investment amount between firms i and j is characterized by the 2-firm function taking the form $\varphi(I_i, I_j) = \omega(I_i) - \omega(I_j)$, where $\omega(I)$ is a 1-firm function (Barrat et al., 2008; Newman, 2010). Fundamentally, it is the effect of how firm i makes its investments in coordination with firm j. Thus, for example, as firm j invests more in doing business with firm i, the latter, in turn, will also make proportionately large amounts of investments[8].

Investment balance is characterized by a vector $\vec{\Theta} = \{I_i^*\}$ for which $\dot{I}_i = 0, \forall\, i = 1, \dots, n$. With differentially coupled investments, the condition $\psi(I_i^*) + \sum_j W_{ij}\varphi(I_i^*, I_j^*) = 0$ reads: $\psi(I_i^*) + s_i\omega(I_i^*) - \sum_j W_{ij}\omega(I_j^*) = 0$, where $s_i = \sum_{k\neq i} W_{ik}$ is the *strength* of firm i in the interlock (Barthélemy et al., 2005), and $\varsigma = \frac{1}{n}\sum_{k=1}^{n} s_k$ is the average strength of the complete network. Introducing a small perturbation $\vec{\eta}$ around $\vec{\Theta}$ and ignoring terms in 2nd-order of smallness, the following investment pattern results: $\dot{\eta}_i = \rho_i\eta_i + \eta_i\sum_j \sigma_{ij}W_{ij} + \sum_j \tau_{ij}W_{ij}\eta_j$. Here, $\rho_i = \frac{d\psi(I_i)}{dI_i}|_{I_i=I_i^*} = \psi'(I_i^*)$; σ_{ij} and τ_{ij} are derivatives of the 2-firm function with respect to its first and second arguments respectively, given by $\sigma_{ij} = \varphi_a(I_i^*, I_j^*) = \omega'(I_i^*) =$

[8] Firms do not make investments in this way unless they are interlocked in a governance structure in which they perform mutually advantageous business transactions in a supply-chain-linked facilitating mode.

U_i, and $\tau_{ij} = \varphi_b(I_i^*, I_j^*) = -\omega'(I_j^*) = -V_j$. These quantities are the model parameters, in terms of which the final equation can be expressed as $\dot{\eta}_i = \rho_i \eta_i + \sum_j \mathbb{G}_{ij} \eta_j$, where $\mathbb{G}_{ij} = s_i U_i \delta_{ij} - V_j W_{ij}$. In matrix notation, the form looks quite simple: $\dot{\vec{\eta}} = \mathbb{N}\vec{\eta}$, where $\mathbb{N}$ stands for the matrix $\rho\mathbb{I} + \mathbb{G}$.

The eigenvalues of $\mathbb{N}$ are of the form $\omega_q = \rho + \lambda_q$ $(q = 1, \ldots, r)$, where λ_q is an eigenvalue of $\mathbb{G}$. In order for the balance to be stable, it is necessary that $\omega_q = \rho + \lambda_q < 0$. Besides, λ_q's are known to be positive semi-definite (Olfati-Saber, 2006). This results in the condition $\rho = \psi'(I^*) < 0$. Importantly, the stable balance condition can be expressed fully in terms of λ_{lar}, the leading eigenvalue of $\mathbb{G}$. Thus, the network's macrostructure is encoded in $\mathbb{G}$ through its weight matrix $\boldsymbol{W}$, which is reflected in the quantity λ_{lar}. By contrast, the network dynamics of firm-specific and the firm-interlinked investments is embedded in the two functions ω and ψ. Through these functions, the dynamics of the underlying network can be maintained[9]. Table 1 summarizes the variables and parameters used in the study.

Table 1: Summary of Variables and Parameters of Firm Investments

Symbol	Explanation
I_i	Investment of firm i
n	Total number of firms in interlocking directorate
m	Total number of ties between pairs of firms in network
$\boldsymbol{W} = \{W_{ij}\}$	Weight matrix of tie strengths between connected firms in network
$\psi(I_i)$	Firm-specific investment of firm i
$\varphi(I_i, I_j)$	Non-symmetric 2-firm function coupling investments of firms i and j
$\omega(I_i)$	1-firm function for firm i's investment to coupled investments
$\vec{\theta}$	Investment balance vector
ρ	Self-induced investment pertaining to firm's investment differential
σ, τ	Firm-interlinked investment pertaining to firm's investment differential
λ_{lar}	Leading eigenvalue of the graph Laplacian

4. Research Setting and Data

For this study, we used board data of publicly listed non-banking, non-finance-sector firms for the year 2014-2017 to construct the sector-specific interlock networks. This period was chosen, because it was relatively stable for the Indian economy, with practically little or no extraordinary events. Moreover, the board interlock structures of our sample of firms did not change significantly over this horizon. Board data included information about company board characteristics, the directors as well as a number of other company attributes for each company in the sample. Specific information about directors on the boards was obtained from data purchased from the Prime Database Group (*http://www.primedatabase.com*). For companies listed on the Bombay Stock Exchange (BSE – *http://www.bseindia.com*) and the National Stock Exchange (NSE – *http://www.nseindia.com*), firm-level data pertaining to capital investment, operational accounting, and performance were obtained from the Prowess database, which is owned, designed, and maintained by the Centre for Monitoring Indian Economy Pvt. Ltd. – (*www.cmie.com*). The data were subsequently cross validated against published annual financial reports of all companies included in the sample. The processed

[9] This point was noted by earlier researchers in the context of general network dynamics (Barrat et al., 2008; Newman, 2010).

data for the window 2007–2015 (inclusive) were then stored in databases constructed and designed for optimized search and retrieval.

There is sufficient early evidence that firms operating within the same industry sector exhibit similar patterns of capital structures (Bradley et al., 1984; Titman & Wessels, 1988). For this study, we grouped our firms by major industry sectors[10]. For inclusive illustration and analysis in this paper, we selected the top four sectors by interlock size. These sectors are fashion (LFC = 101; SNA = 151); manufacturing (LFC = 117; SNA = 140); transport (LFC = 99; SNA = 128); and food (LFC = 93; SNA = 122), where the figures in parentheses indicate the sizes of the LFC and SNA interlock networks in the corresponding sectors (see Table 2 for details).

Historically, LFCs have played a critically important role in India's economy. Because of the country's long tradition of family- and community-controlled firms (Kumar & Singh, 2013; Ray et al., 2018; Selarka, 2005), there is a strong connection linking these families, communities, and businesses in India (Bajpai, 2016). Nevertheless, it has sometimes been criticized that an excessive dominance exercised by these firms over the market reduces overall market efficiency and performance (Gollakota & Gupta, 2006). On the other hand, market liberalization and constructive steps taken subsequently by market regulators such as, the Securities and Exchange Board of India or SEBI, have ameliorated the governance situation in the corporate sector. This has given rise to a significant flow of capital investments from SNAs to grow and expand in order to compete with market controlling LFCs through their board influence, range, and subsidiary deployments in the market (Bajpai, 2016).

To collect data for the sample of firms for SNA and LFC interlocks, we excluded all Indian subsidiaries of foreign multinationals as well as financial services and banking firms that adhere to different accounting standards. In conformity with the practice followed by prior researchers (Claessens & Fan, 2002; Singla et al., 2014; Villalonga & Amit, 2006; Ray et al., 2018), we identified a firm as LFC if the primary family has a vested stake amounting to 20% or higher in the firm, in which a member of this family sits on the firm board and/or functions as the board chair.

Our primary study variable is capital investment of firms. Following earlier convention (Ascioglu et al., 2008; Coles et al., 2006; Martin et al., 2013), we computed it as the total amount of spending on all of the following items: Land and building; plant and machinery; computers and electrical assets; transport, communication equipment, and infrastructure; furniture, social amenities, and other fixed assets[11]. Finally, groups of firms were compared based on the four standard performance indicators: Return of equity (ROE); Return on assets (ROA); Tobin's Q (TQ); Price-earnings multiples (PE).

5. Computations

In keeping with behavioral isomorphism, we employed two separate models for the 2-firm function but keep the firm-specific investment function the same in both cases[12].

5.1. Firm-specific investments

To find the form of the firm-specific function, we examined an empirical time series of the capital expenditures of all non-interlocked isolates in every industry sector included in the sample. In Figure

[10] The sectors are listed on the National Portal of India (https://www.india.gov.in).

[11] Of course, several other components may be aggregated into the total realizable capital expenditures of firms. However, for the present study, the items listed above provide an adequate approximation.

[12] The bulk of the numerical work in this study was performed using routines written in the C++ programming language and in Matlab R2013a (8.1.0.604). A few computations for the large-scale network metrics were carried out with the Pajek 4.04 (Batagelj & Mrvar, 2015) and the Ucinet 6 (Borgatti et al., 2002) software packages.

1, these plots are illustrated for two sectors: Fashion (A_2B_2) and manufacturing (A_1B_1). The phase-plane dynamics, exhibited in Figure 2, is identical for both. The regions B_1 and B_2 correspond to actual time series data obtained from the manufacturing and fashion sectors respectively. The regions A_1 and A_2 correspond to unspecified initial-period investments[13]. For the selected firm groups in the samples, such early data were unavailable. Nevertheless, the typical early-time behavior exhibits either growth or decline in a nearly linear fashion before a saturation region is reached (Almeida & Campello, M. 2007; Hillier & McColgan, 2006). In time, the growth phase corresponds to incrementally rising investment amounts, and the decline phase corresponds to incrementally falling ones, assuming that investments started at some initial time $t = 0$. The reason is that, the near-linear investment growth or decline persists only over a fairly short initial window, after which it begins to saturate. Following on this clue to firm's investment trends, the firm-specific function is modeled as $\psi(I_i) = \alpha(1 - I_i)$, where α is a positive constant. In this case, the network reaches balance at $I^* = 1$[14]. On the interval $(0,1)$, $\psi(I) > 0$: the flow carries the phase point to the right toward $I^* = 1$. On $(1, \infty)$, $\psi(I) < 0$: the flow carries it to the left toward $I^* = 1$. In either case, the phase point drifts toward $I^* = 1$ and settles right there. The *characteristic time scale* of convergence is given by the quantity α^{-1}, which characterizes the time for $I(t)$ to vary significantly around $I^* = 1$.

Figure 1. Time-series of firm-specific investments (unscaled) of non-interlocked isolates in fashion (lower curve) and manufacturing (upper curve)

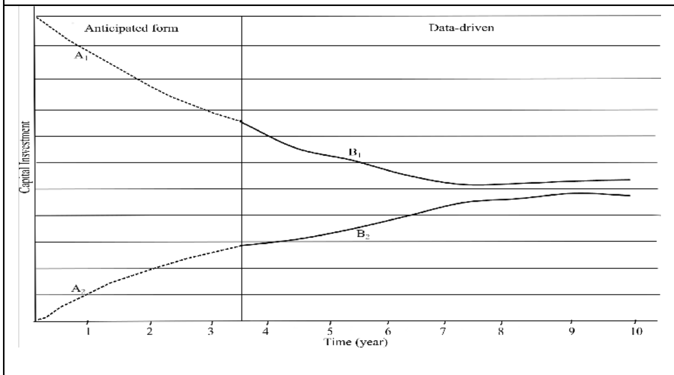
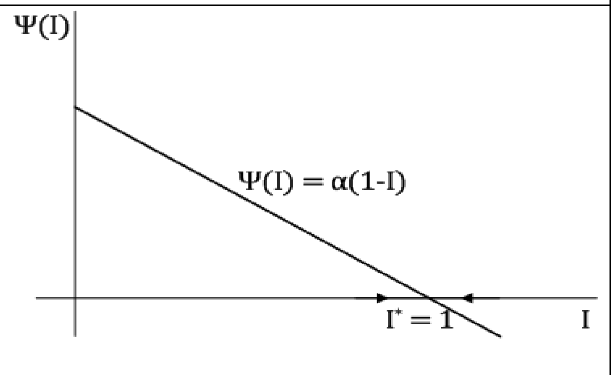


Figure 2. Phase plane diagram corresponding to Figure 1



5.2. Firm-interlinked investments

Early firm-interlinked investment dynamics is marked by sporadic capital expenditures during by a firm's initial negotiations and adjustments with its supply-chain partners. Since this behavior does not show isomorphism, it is not included in the study. Interest, however, focuses on the long-run balance, for which two separate models for the 2-firm function are employed.

Model 1. By its very construction, the 2-firm function embodies a deficit: $\varphi(I_i, I_j) = \omega(I_i) - \omega(I_j)$. When the interlocked firms operate in supply-chain-linked modes, a practically reasonable 1-firm function can be represented as $\omega(I_i) = \beta I_i(1 + I_i)^{-1}$, where β is a positive constant. As $I \to 0$, one has $\omega \sim I$, and as $I \to \infty$, it is seen that ω approaches β asymptotically. Since $\omega'(I^*) = \beta > 0$, the trivial fixed point

[13] The initial periods are characteristic of the investment behavior of a firm immediately after the inception of specific projects or just after it has been listed on a stock exchange.

[14] The application-specific scales used in firms' investment amounts are not of any particular significance for the present and subsequent discussions.

$I^* = 0$ is inherently unstable. Henceforth, this impractical condition will not be of any concern to this study. The actual form of the 2-firm function is $\varphi(I_i, I_j) = \beta \frac{I_i - I_j}{(1+I_i)(1+I_j)}$. In this model, the balance emerges at $I^* = 1$, and to reach stability, one obtains $\lambda_{lar} < \frac{4\alpha}{\beta}$.

Model 2. In this model, the 1-firm function is taken to be $\omega(I_i) = I_i(\gamma + I_j - I_i)$, where $I_i, I_j > 0$ are the investment levels of firms i, j respectively, and γ is a positive constant. Physically, this form embodies a *synergistic* investment relationship between firms i and j. This signifies, for a definite level of j's investments, the corresponding investment amount of i rises initially but declines subsequently. More specifically, for a given value of I_j, i's amount varies quadratically in I_i that is zero when $I_i = \{0, \gamma + I_j\}$ and reaches a maximum of $\frac{1}{4}(\gamma + I_j)^2$ at $\tilde{I}_i = \frac{1}{2}(\gamma + I_j)$. This yields the 2-firm function $\varphi(I_i, I_j) = (I_i - I_j)(\gamma - I_i - I_j)$. The fixed point for the firm-specific component ($\vec{I}^* = \vec{1}$) is a large-scale solution in this model. Further, $\omega'(I^* = 1) = \gamma - 1$, $\psi'(I^* = 1) = -\alpha$, and stability is given by the condition $\lambda_{lar} < \frac{\alpha}{\gamma - 1}$, where $\alpha, \gamma > 0$. Additionally, the symmetric graph Laplacian has real, non-negative eigenvalues (Anderson & Morley, 1985; Li & Zhang, 1998), imposing the further restriction that $\gamma > 1$, so that, ultimately, $0 < \gamma < \left(\frac{1}{\lambda_{lar}}\right)\alpha$. Assuming that $\psi(I_i^*) = 0$ has a solution $I_i^* = s$, one has $I_j^* = \gamma - s$. Since $I_j^* \neq s$, there is a further restriction on γ: $\gamma \neq 2s$.

5.3. Numerics

The network's structural computation rests on the graph Laplacian matrix $\mathbb{G}$. Denote the leading eigenvalue of $\mathbb{G}$ by λ_{lar}^{act}. The stationarity condition in model 1 is then given by $\lambda_{lar}^{act} < \frac{4\alpha}{\beta}$, and the basin boundary is given parametrically by the equation $\beta = (\frac{4}{\lambda_{lar}^{act}})\alpha$. In model 2, the corresponding condition is $\lambda_{lar}^{act} < \frac{\alpha}{\gamma - 1}$, and the basin boundary is given by $\gamma = \left(\frac{1}{\lambda_{lar}^{act}}\right)\alpha + 1$. We computed the eigenvalues of $\mathbb{G}$ by tridiagonal reduction using Householder algorithm and subsequently by the diagonalization of the reduced matrix using QL algorithm (Press et al., 1992).

5.4. Calibration

Because their real population distributions of the model parameters were unknown, we performed Monte Carlo simulations centered on real market data, considering them as the true population (Efron & Tibshirani, 1993; Mooney & Duval, 1993). To do this, we selected the parameters so that the squared-errors $(I_i - I_i^{act})^2$ were minimized over the entire sample observations. Introducing a partition of the full time window by discrete time points $(t_1, \dots, t_K)$, we then added the errors at each time point, weighted the quantity by the measurement error σ_{I_i} of each I_i, and generated an objective function of the form $\chi^2 = \sum_{i=1}^{n} \sum_{t_j} (\frac{I_i(t_j) - I_i^{act}(t_j)}{I_{S_i}})^2$, where n is the number of variables, and t_j is the number of sample data points. Finally, we estimated the parameters by minimizing χ^2 by the Levenberg-Marquardt method (Press et al., 1992). The steps are as follows:

1. Using actual market data, construct the graph Laplacian $\mathbb{G}_0$.
2. From $\mathbb{G}_0$, estimate the parameters for one stable state of the dynamics. Let Θ_0 be the parameter set $\Theta_0 = (\alpha_0, \beta_0, \gamma_0\}$.
3. Resample the tie weights of the interlock network uniformly at random with replacement.
4. Choose the same number of sampled tie weights at a time and assign them to an initially unweighted configuration of the network.
5. Compute a bootstrapped $\mathbb{G} = \mathbb{G}_1$ for this network.
6. Use $\mathbb{G}_1$ as $\mathbb{G}_0$'s surrogate and find the parameter set $\hat{\Theta}_1$ for a stable network configuration.

7. Repeat steps 2–5 as many times as desired to generate the parameter sampling distribution $\{\hat{\Theta}_2, \dots, \hat{\Theta}_B\}$.

After the successful termination of this procedure, we computed the relevant parameter confidence intervals by the percentile method (Joshi et al., 2006): If $\hat{\Theta}^{(\alpha)}$ represents the $100(1-\alpha)$ percentile, then the confidence interval is given by $\mathbb{I} = (\bar{\Theta}_l, \bar{\Theta}_u) = (\hat{\Theta}^{\frac{\alpha}{2}}, \hat{\Theta}^{1-\frac{\alpha}{2}})$.

6. Results and Discussions[15]

6.1. Macro Features

The two networks employed in this study are the board interlocks of LFCs and SNAs, restricted to separate sectors of the industry, where a sector is specified by the sector in which the primary (focal) firm operates. Table 2 displays the values of the macrostructure metrics of these networks. As already mentioned before, results from four of the largest sectors according to the sizes of their interlocks are discussed in this paper. These sectors are fashion, manufacturing, transport, and food.

Small values of the network density for both LFC and SNA interlocks, computed using the formula $\rho = \frac{m}{\frac{1}{2}n(n-1)}$, indicate the sparseness of these networks (Wasserman & Faust, 1994). The mean degrees lie in the range of 1.9 – 3.8, and the mean strengths per vertex in the range 2.5 – 5.2. The values for SNAs are slightly higher than those for LFCs. Overall, they signify that connection centralities of the interlocked firms are somewhat low, a result that is further corroborated by the small value of the degree centralization of the networks. The centralization measures the extent to which interlocking ties among the firms are bound to the highly connected firm boards and is computed by the formula $\sigma_\vartheta = \frac{\sum_{i=1}^{n}(k_{max}-k_i)}{\max[\sum_{i=1}^{n}(k_{max}-k_i)]}$, where k_{max} is the largest degree, k_i is the degree of firm i, and $\max[\dots]$ gives the theoretical maximum sum of differences in the degrees in the network (Wasserman & Faust, 1994). The low value is indicative of an interlock density that does not depend significantly on the highly connected firms. The large-scale topology of the networks shows that this characteristic is similar across LFC and SNA interlocks.

The betweenness centrality β_i of firm i is an indicator of the extent to which the firm lies on paths between other firms and is computed using the formula $\beta_i = \frac{1}{\frac{1}{2}(n-1)(n-2)}\sum_{j<k}\frac{n_{jk}^i}{n_{jk}}$, , where n_{jk}^i is the number of geodesics (shortest paths) connecting firms j and k that pass through firm i, and n_{jk} is the total number of geodesics between j and k (Wasserman & Faust, 1994). For both LFCs and SNAs, the average betweenness scores are much higher in manufacturing, transport, and food than those in the fashion. This makes perfect sense, because the majority of the fashion firms do not span multiple other firms either within or across sectors. By contrast, the specific nature of business transactions in transport, manufacturing, and food makes most firms in these sectors overlap with multiple other firms. Moreover, in all cases, the average betweenness of LFCs is somewhat lower than that of SNAs.

Next, we measured the geodesic distance between two firms in terms of the number of interlocks between them, and on averaging over all firms, the mean distance is computed (Wasserman & Faust, 1994). In a small-world network, this distance scales as $\ln(n)$ (Newman 2003). One may compare this with the corresponding metric of a random network consisting of n firms and with a mean degree of ϑ, where the distance scales as $l_{rand} \sim \frac{\ln(n)}{\ln(\vartheta)}$ (Watts & Strogatz, 1998). A comparison

[15] For considerations of space, we present complete results for the manufacturing sector only, which serves the purpose of illustration. Results for the other sectors are similar. Nevertheless, we provide aggregate results for these sectors in the appropriate places.

between the mean distances of the networks under consideration and those of their random counterparts is a test for their small-worldliness (Watts, 1999; Watts & Strogatz, 1998). Additionally, the diameters of LFCs came out to be slightly larger than those of SNAs.

Table 2: Large-scale interlock network metrics for LFC and SNA firms in four sectors: Fashion; Manufacturing; Transport; Food

Metric	Sectors								Explanation
	Fashion		Manufacturing		Transport		Food		
	LFC	SNA	LFC	SNA	LFC	SNA	LFC	SNA	
n	101	151	117	140	99	128	93	122	Network size (number of vertices)
m	116	185	149	177	118	242	128	154	Number of edges in network
ρ	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.02	Network density
ϑ	2.01	2.45	1.93	2.53	2.33	3.78	2.11	2.52	Mean network degree
ς	2.91	3.67	2.71	3.60	3.06	5.17	2.46	3.95	Mean network strength
σ_{ϑ}	0.02	0.04	0.05	0.05	0.03	0.06	0.03	0.05	Degree centralization
β	2.7	3.2	10.1	15.7	16.3	23.9	11.4	12.7	Mean betweenness centrality (scaled)
l	5.93	4.61	6.01	5.54	6.07	4.43	5.06	5.16	Mean geodesic distance (unweighted network)
l_{rand}	6.81	5.60	7.24	5.32	5.43	3.65	6.07	5.20	Mean geodesic distance (random network)
δ	16	13	14	13	12	11	15	13	Network diameter
CC	0.53	0.51	0.39	0.35	0.38	0.31	0.50	0.41	Global clustering coefficient
CC_{rand}	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	Global clustering coefficient (random network)

Finally, the fraction of transitive triads in a network is a measure of its clustering coefficient (CC). This is the probability that any two randomly selected adjacent firms of a focal firm are themselves first neighbors. We computed the CC using the Watts-Strogatz formula (Watts & Strogatz, 1998). Again, a common comparison benchmark is the CC of the corresponding random network, given by the formula $CC_{rand} = \frac{\vartheta}{n}$ (Newman, 2003). As evident from Table 2, for both LFCs and SNAs, the CC's far exceed the values for their random networks. This lends additional support for the small-worldliness of both classes of networks (Watts, 1999), although the effect is slightly more prominent in SNAs.

5.2. Investment Structures

5.2.1. Simulations of models 1 and 2

As discussed earlier, the balance condition in model 1 is achieved at $I^* = 1$ (in appropriate units). The basin boundaries separating the regions of stability and instability of the underlying dynamics represented in parameter space are displayed in Figure 3 for all interlocks. The relative significances of the parameters α and β are characterized by the values of the slopes of the straight lines that demarcate the two regions, which are shown in parentheses in the legend. The entire region lying below the basin boundary is stable, and the one above it is unstable. Any point lying exactly on the line is metastable. SNA basin boundaries lie above LFC boundaries. Thus, for SNAs, more flexibility is available in the choice of the α's and the β's. To increase visual clarity, different scales for the vertical and horizontal axes in the figure give the appearance of a much-magnified stability region. In numerical terms, the regions are actually quite small. This signifies that, small perturbations in the relative significances of α and β in a stable region very close to the basin boundary might cause the system to slide to the unstable region. In model 2, stability again emerges at $I^* = 1$. The results are displayed in Figure 4. The stability regions are comparatively smaller in this model, which renders the relative distributions of α and γ even more delicate than in the previous model.

Figure 3. **Basin boundaries of interlock networks in model 1**

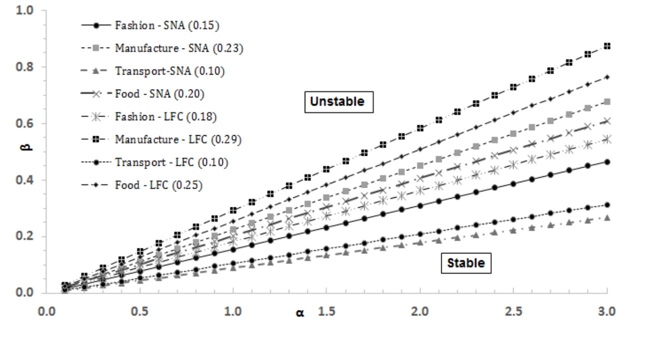
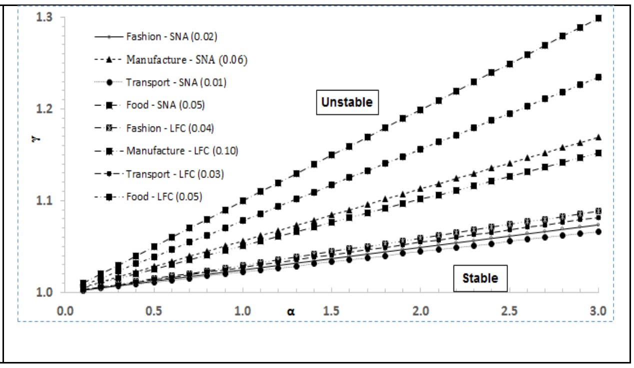


Figure 4. **Basin boundaries of interlock networks in model 2**



5.2.2. Parameter significance

It is clear from the foregoing analysis that the relative significance of the two modes of investments is limited by the size of the stability regions in parameter space. As for the first model, the investment dynamics becomes unstable when β becomes sufficiently large to make $4(\frac{\alpha}{\beta})$ smaller than the Laplacian's largest eigenvalue. This corresponds in practice to a situation in which interlinked investments significantly dominate firm-specific ones. It has the effect of making investments in high-mean-strength, low-density networks unstable. The typical mean strength of the present networks is not overly high (Table 4). If the investment dynamics is to operate in the desired configuration, the interlinked component must be appropriately strategized. The situation is encouraging in a stable-balance configuration, because a strong, interlinked component greatly facilitates individual firms to strategize their capital expenditures quite selectively. Starting from an unbalanced configuration at some time, this has the potential to eventually raise firm-specific investments to a new level, where a stable balance obtains in the underlying investment dynamics.

5.2.3. Monte Carlo simulations

Figure 5. **Manufacturing sector bootstraps of α and β in model 1 for the SNA interlock**

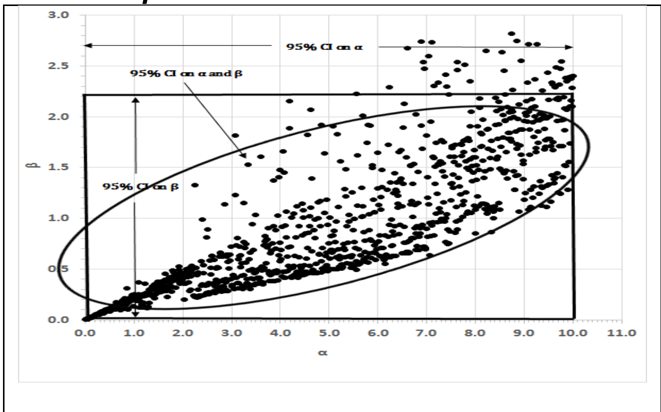
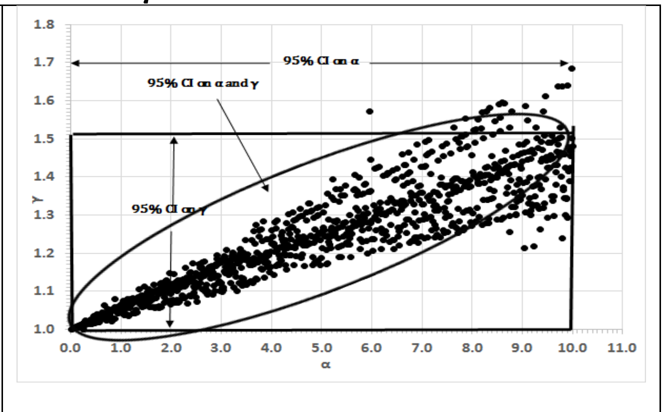


Figure 6. **Manufacturing sector bootstraps of α and γ in model 2 for the SNA interlock**



In the results of the two-parameter Monte Carlo simulations of models 1 and 2, displayed in Figures 5 and 6 for the manufacturing sector of SNA interlock, there is a clear indication of a correlation between the model parameters. For example, in Figure 5, the α-β correlation in model 1 is about 0.84 (significant at 95%). For transport, fashion, and food, these correlations are, respectively, 0.77, 0.79, and 0.88, all significant at 95%. Three confidence intervals (CI) are shown in the figure, at the same level of significance. A band enclosed by two vertical lines characterize the 95% CI for α independent of β, and by two horizontal lines characterize a 95% CI for β independent of α. The joint distribution of α and β is represented by an ellipse for a 95% CI (Press et al., 1992). Similar plots are shown for model 2 in Figure 6, where the α-γ correlation is close to 0.91 (significant at 95%). Using the average value $\bar{\Theta}$ of a parameter, the range Λ and the shape Γ of its CI can be computed by using the formulas $\Lambda = \bar{\Theta}_u - \bar{\Theta}_l$ and $\Gamma = \frac{\bar{\Theta}_u - \bar{\Theta}}{\bar{\Theta} - \bar{\Theta}_l}$ (Joshi et al., 2006). In this case, $\Gamma > 1.0$ gives a shorter distance from $\bar{\Theta}$ to Θ_l than from $\bar{\Theta}_u$ to $\bar{\Theta}$. By contrast, for a normal distribution, $\Gamma = 1.0$, the distribution being symmetric about $\bar{\Theta}$. In model 1, nearly 95% of the cases had $\Gamma \approx 1.43$, and for model 2, 95% of the cases had $\Gamma \approx 0.94$. Linearity is therefore ensured for manufacturing, although there is an indication of some slight deviation from linearity in model 1. For transport, fashion, and food, we obtained, respectively, $\Gamma \approx 0.92$ (model 1), $\Gamma \approx 0.94$ (model 2); $\Gamma \approx 1.17$ (model 1), $\Gamma \approx 0.91$ (model 2); $\Gamma \approx 1.28$ (model 1), $\Gamma \approx 1.09$ (model 2). These are, therefore, quite similar to those for manufacturing.

5.2.4. Model Use

With the models calibrated as described above, we next proceed to perform a comparative analysis of the market and the model behavior of aggregate investments of the firms in SNA and LFC interlocks. For considerations of space, we only consider the case of manufacturing in model 1. First, we perform a computation of the deviation amounts, in real time, of the average market values of firm investments from the stable values predicted by the models. Using the formalism described before, we perform the computations by employing the following differential equation: $\dot{\eta}_i = -\alpha\eta_i + \beta\frac{\eta_i}{(1+I_i^*)^2}\sum_{k\neq i} W_{ik} - \beta\sum_j \frac{W_{ij}\eta_j}{(1+I_j^*)^2}$. The predicted values of the investments are then obtained from the relation $\hat{I}_i(t) = I_i^* + \eta_i(t)$, and the amount of deviation for firm i is calculated as $\Delta I_i(t) = I_i^{act}(t) - \hat{I}_i(t)$, where $I_i^{act}(t)$ is the actual, market value of the investment amount of firm i at period t. The procedure can be summarized as follows:

1. Numerically integrate the above equation over a predefined partition consisting of n time points $(t_1, t_2, \ldots, t_n)$ to obtain the predicted values.
2. Calculate deviations by taking the difference of predicted amounts and the actual market values at the corresponding time points.
3. Select a pair of parameter values, say $\vec{\theta}_k = (\alpha_k, \beta_k)$, from the stable region in parameter space.
4. Using these values in the numerical integration, compute the deviation amount $\Delta I_i(t_k) = I_i^{act}(t_k) - \hat{I}_i(t_k)$ at time $t = t_k$.
5. At each selected time point, compute the average deviation over a sufficiently large number, say M, of sample points selected uniformly at random from the stable region in parameter space, averaged over all the firms in the network, yielding the quantity: $< \Delta I(t_k) > = \frac{1}{Mn}\sum_{s=1}^{M}\sum_{i=1}^{n} \Delta I_i^{\vec{\theta}_s}(t_k)$.

Figures 7 exhibits the results of these computations. The horizontal axis represents the time (in years) for the period 2007–2015. The vertical axis shows the relative absolute deviations (RAD) computed as a percent difference between the stable values predicted by the model and the median market values of investments of firms for each year. Over practically the entire window, the deviations are found to be larger for LFCs, close to 46%, than for SNAs, close to 20%. Deviations of approximately the same order were also found for transport, fashion, and food: Transport (LFC: 41%; SNA: 21%); Fashion (LFC: 35%; SNA: 19%); Food (LFC: 46%; SNA: 24%).

However, it is important to remember that the stable values more accurately reflect the investment dynamics incorporated into the model unfolding on the interlocks, which is adapted to longer horizons than the present nine-year period shown here. Besides, since the market often reacts unpredictably to exogenous influences, large deviations between the actual market values and the predicted values are not entirely unexpected and do appear from time to time.

Figure 7. RAD values in model 1 (manufacturing)

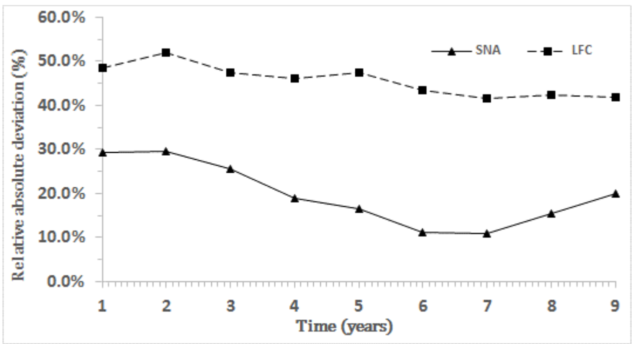
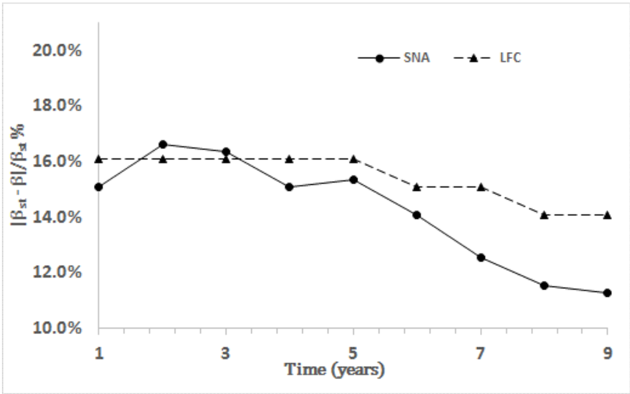


Figure 8. β-errors in model 1 (manufacturing)



The second set of computations is based on a different approach. Here, interest focuses on the study of parameter deviations in *real* time from their stable values in parameter space. The procedure runs as follows:

1. For a specific choice of parameters, say $\vec{\theta} = (\alpha, \beta)$, not necessarily selected from the stable region in parameter space, compute the predicted value $\hat{I}_i^{\vec{\theta}}(t_k)$ at time $t = t_k$ using the model.
2. *Imagine* that it is the *actual* market value at that time. In other words, for firm i, set $\hat{I}_i^{\vec{\theta}}(t_k) = I_i^* + \eta_i^{\vec{\theta}}(t_k) = I_i^{act}(t_k)$, so that $\eta_i^{\vec{\theta}}(t_k) = I_i^{act}(t_k) - I_i^* = X_i$, a known quantity.
3. Taking an initial deviation, say $\eta_i(0) = \eta_0$, numerically integrate the model differential equation and obtain $\eta_i^{\vec{\theta}}(t_k) = f_i(\vec{\theta}, \mathrm{F}) = X_i$, where $f_i(\vec{\theta}, \mathrm{F})$ is a function of the parameter vector $\vec{\theta}$ and other known quantities, represented symbolically by F.
4. To study the behavior of only one parameter at a time, randomly select a value of α from the stable region in the parameter space, say $\alpha = \alpha_{st}$, and use it in the above equation to compute the corresponding value of β.
5. Compare this β value with the average of all permissible values of β_{st} corresponding to the fixed but randomly selected α_{st} from the stable region in parameter space.
6. Compute the β-error as the deviation amount $\Delta\beta = \beta_{st} - \beta$, where $\beta_{st} = (\frac{2}{\lambda_{lar}})\alpha_{st}$.
7. The foregoing procedure is now executed repeatedly at each time point $t_i, i = 1, \ldots, n$.

The results for both SNAs and LFCs are displayed in Figure 8. The β-errors lie in the range of $11 - 17\%$. These are not large, signifying that there is much greater flexibility in the selection of a wide range of α_{st} from α's stable region in parameter space. Of course, for some periods, the β-errors may actually turn out to be large. Should this be the case, it would be necessary to turn the argument around and look for reasonably small α-deviations by selecting appropriate β_{st} from β's stable region in parameter space. It is also evident that, overall, the β-errors for SNAs are smaller than those of LFCs. SNAs seem to have much greater flexibility in the choice of their supply-chain network of partners through the strategic appointment of independent directors on their boards. By contrast, LFCs may not always benefit from this flexibility of choice. Their boards are often overburdened by the presence of a large fraction of extended family members of their promoters. Some of these independent, nonexecutive directors are from firms in unrelated sectors of the market and do not have first-hand experience in the market domain in which the focal firm operates. They play only decorative roles on the board or pay lip service to the decisions taken by the promoters. This results in reduced investment efficiency and low market performance (Bajpai, 2016; Gollakota & Gupta, 2006; Kumar & Singh, 2013). The β-errors for transport, fashion, and food lie, respectively, in the ranges of $9-21\%$, $13-26\%$, and $11-23\%$. Again, these errors are not overly large and comparable in magnitude with those for manufacturing.

5.2.5. Firm Performance

With the capital investment dynamics unfolding on the firm interlocks, we first computed the stable investment values of the firms according to the underlying dynamics. Next, we segregated all firms in SNA and LFC interlocks into two groups. Group 1 (G_1): Firms that attained stability according to the underlying dynamics; Group 2 (G_2): Firms that did not attain stability. We then compared the firms in these two groups on their ROE performance and computed the firm performance differential using a quantity defined as $\Delta x = \frac{x_{st}-x_{\overline{st}}}{x_{st}+x_{\overline{st}}}$, where x_{st} stands for the yearly average value of ROE for a firm that has reached stability, and $x_{\overline{st}}$ is the value for a firm that has not reached stability.

Figure 9. Performance (ROE) differentials (manufacturing)

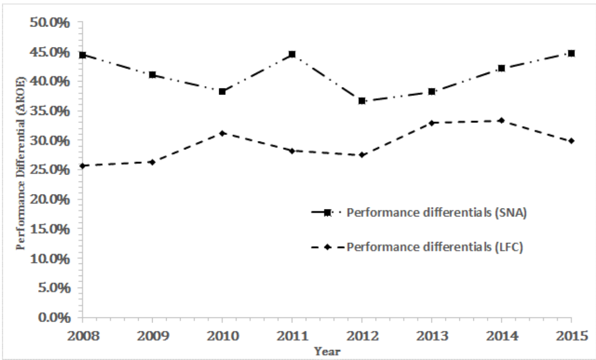
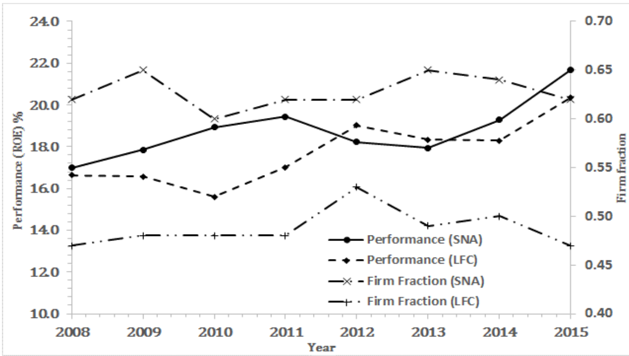


Figure 10. Performance (ROE) of firms (manufacturing)



Figures 9 and 10 display the results of the performance comparison study for the manufacturing sector interlocks over a window of 2008-2015 inclusive. As Figure 9 shows, for both SNA and LFC interlocks, G_1 had consistently higher performance scores than G_2 in all the years included in the window. Besides, over the years, the performance differentials for SNAs are somewhat higher (about 12% on the average) than those for LFCs. Figure 10 displays the average ROE performance scores of the G_1 firms for both SNA and LFC interlocks. The average performance of the G_1 group of firms of SNA interlock is consistently higher than that of the G_1 group of firms of LFC interlock, except in two years where LFC performance score is only 3% higher. We also obtained similar results for transport, fashion, and food. The G_2 firms are not included in the performance comparison study, because their performance scores are much lower, in any case, than those of the G_1 firms for both interlocks. In Figure 10, the right-hand (secondary) vertical axis shows the fraction of firms within the group that attained stability according to the underlying investment dynamics. Fractions of SNAs are clearly much larger than fractions of LFCs in all periods. It is curious that several LFCs in the G_2 group exhibited performance closely comparable to the performance of the firms in the G_1 group. Such is not the case for SNAs.

5.2.6. Robustness Checks and Supplementary Analysis

In order to gain a deeper insight into the current findings, we repeated all of the previous analyses using supplementary model 2 and additionally performed robustness checks for the results. To this end, we compared SNAs and LFCs in the two groups G_1 and G_2 on three additional measures of performance: ROA; TQ; and PE. As before, we computed, in each of the remaining three sectors (fashion, transport, and food) the firm performance differentials Δx where $x = \{ROA, TQ, PE\}$. The results obtained from these analyses are quite similar to the above results for the ROE measure in the manufacturing sector. However, in each of the years within the selected time window, the firm fractions turned out to be somewhat large for manufacturing and fashion compared with the values obtained for transport and food. For considerations of space, these results are not included here.

6. Limitations and Conclusion

SNAs engaging in supply-chain networked transactions make investments in capital expenditures both individually and in cooperative association with their partner firms. Investments to meet internal demands of a firm are specific to the firm. By contrast, when functioning in interlinked modes, firms strategically align their investments in order to accommodate interfirm specificities typical in associative operations, with each firm in the interlinking chain having its portfolio of investment items.

From the current perspective, firm investments are most effective when a harmonizing balance exists between the firm-specific and the firm-interlinked forms of investment. In Indian firms, board interlocks are essential channels through which firms operate within supply-chain linkages, wherein a group of firms can adjust their investments for streamlining production or service operations as well as for minimizing fluctuations in their supply chains. Ultimately, it helps the firms to deal more effectively with uncertain demands or erratic supply problems. In some situations, financial managers are prone to plan investments under pre-set constraints. Moreover, many expenditure items are not fixed initially, and different firms tend to spend widely unequal proportions of expenditure on these items. It then becomes difficult to sustain such investments over long periods, because instabilities invariably develop in their financial systems. This is the primary justification for the use of the simulations in this study.

The present framework is predicated upon a resource-dependence view that SNAs strategically choose directors on their boards from their potential partner firms in order to have access to the critical resources of these firms. In point of fact, this is largely true for our sample of firms. Nevertheless, institution scholars have pointed out that the environments of firms are not always dependable, in that interfirm ties give rise to new dependencies and shift the balance in the firm relationship structures, such as when partner firms compete with one another for control over critical resources (Pfeffer & Salancik, 1978; Hallen et al., 2014). If the firms in question are actually competing in some sectors, opportunistic firm behavior may result. Thus, while competing firms collaborate for shared benefits, they can simultaneously behave opportunistically to produce a power imbalance and force a partner into an unfavourable position (Agarwal et al., 2010; Gulati & Singh, 1998)[16]. This behavior can be incorporated into our study by employing a suitable economic utility function.

It is true that interlocking directorates are an effective way to strengthen strategic ties and to effectively exploit network advantages. Nevertheless, positive strategic advantages in investment decisions and increased competitiveness can also result from cooperation with strategic partners, even without shared directors on the board. Thus, in many cases, partnerships and strategic ties

[16] For example, "swimming with a shark" is a situation in which a young, rising firm forges a tie with an established large firm that is potentially attractive to it and yet dangerously rivalrous (Diestre & Rajagopalan, 2012; Hallen et al., 2014; Katila et al., 2008).

signify an increase in knowledge, resources and thus also in market opportunities, even without interlocking directorates. These additional benefits can be leveraged to bolster the tie strengths used in the present formalism. On a different note, many of the adversities and challenges confronted by SNAs are the same as or are very similar to the difficulties faced by LFCs in India. These, for instance, may arise from market conditions, government decisions and policies, global economic conditions, as well as man-made or natural calamities, such as the recent Covid-19 pandemic that played havoc with the national economy. LFCs, because of their large size and financial strength, have much better advantages to deal with these issues than SNAs. Nevertheless, it may also be the case that SNAs, due to their small size and less bureaucratic structure, have advantages in some areas compared to LFCs. These issues are likely to have an influence on the performance indicators considered in the present study.

We mentioned earlier that over short initial periods, investment coordination between firms might be incomplete and somewhat unsteady. This is perfectly normal. However, because we were primarily concerned with long-run, steady-state investment behavior, our model applied best to long time frames when initial interfirm instabilities in coordinated investments have become negligible. Another issue concerns the absence of cross-level interactions between the two types of investment functions considered here. In actual practice, firm-specific investments depend somewhat on the interlinked ones. Therefore, to make the framework more general and robust, interaction effects should be included at the next higher level. This procedure, albeit computationally intensive, is conceptually clear. As far as we can see on the strength of empirical evidence at this time, we do not have a convincing causal effect of interactions between firm investments on their performance. Additional work in this direction is currently underway.

References

Almeida, H., & Campello, M. 2007. Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies*, 20(5), 1429-1460.

Anderson, W. N., & Morley, T. D. (1985). Eigenvalues of the Laplacian of a graph. *Linear and Multilinear Algebra*, 18(2), 141-145.

Ascioglu, A., Hegde, S. P., & McDermott, J. B. (2008). Information asymmetry and investment–cash flow sensitivity. *Journal of Banking & Finance*, 32(6), 1036-1048.

Bajpai, G.N. 2016. The Essential Book of Corporate Governance. Sage India, New Delhi.

Baiman, S., & Rajan, M. V. 2002. Incentive issues in inter-firm relationships. *Accounting, Organizations and Society*, 27(3), 213-238.

Bandyopadhyay, A., & Das, S. K. (2005). The linkage between the firm's financing decisions and real market performance: A panel study of Indian corporate sector. *Journal of Economics and Business*, 57(4), 288-316.

Barrat, A., Barthélemy, M., & Vespignani, A. (2008). *Dynamical Processes on Complex Networks*. Cambridge University Press, Cambridge, UK.

Barthélemy, M., Barrat, A., Pastor-Satorras, R., & Vespignani, A. (2005). Characterization and modeling of weighted networks. *Physica A*, 346(1–2), 34-43.

Batagelj, V., & A. Mrvar. 2015. *Pajek—Program for Large Network Analysis*. Retrieved October 2, 2015 (http://vlado.fmf.uni-lj.si/pub/networks/pajek).

Bengtsson, M., & Kock, S. (1999). Cooperation and competition in relationships between competitors in business networks. *Journal of Business & Industrial Marketing*, 14(3), 178-194.

Bidault, F., & Salgado, M. 2001. Stability and complexity of inter-firm co-operation: The case of multi-point alliances. *European Management Journal*, 19(6), 619-628.

Booth, L., Aivazian, V., Demirguc-Kunt, A., & Maksimovic, V. (2001). Capital structures in developing countries. *Journal of Finance*, 56(1), 87-130.

Borgatti, S. P., Everett, M. G. & Freeman, L. C. 2002. *Ucinet 6 for Windows: Software for Social Network Analysis*. Harvard, MA: Analytic Technologies.

Bradley, M., Jarrell, G. A., & Kim, E. H. (1984). On the existence of an optimal capital structure: Theory and evidence. *Journal of Finance*, 39(3), 857-878.

Carney, M. (2005). Corporate governance and competitive advantage in family-controlled firms. *Entrepreneurship Theory and Practice*, 29(3), 249-265.

Chakrabarti, R., Megginson, W. L., & Yadav, P. K. (2008). Corporate governance in India. *Journal of Applied Corporate Finance*, 20(1), 59-72.

Claessens, S., & Fan, J. P. H. (2002). Corporate governance in Asia: A survey. *International Review of Finance*, 3(2), 71–103.

Coles, J. L., Daniel, N. D., & Lalitha N. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, 79(2), 431-468.

Cousins, P. D., & Menguc, B. (2006).The implications of socialization and integration in supply chain management. *Journal of Operations Management*, 24(5), 604-620.

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007).The severity of supply chain disruptions: Design characteristics and mitigation capabilities. *Decision Sciences*, 38(1), 131-156.

Daily, C. M., & Dollinger, M. J. 1992. An empirical examination of ownership structure in family and professionally managed firms. *Family Business Review*, 5(2), 117-136.

Efron, B., & Tibshirani, R. J., 1993. *An Introduction to the Bootstrap*. Chapman and Hall, NY.

Elango, B., & Pattnaik, C. (2007). Building capabilities for international operations through networks: a study of Indian firms. *Journal of International Business Studies*, 38, 541-555.

Gollakota, K., & Gupta, V. (2006). History, ownership forms and corporate governance in India. *Journal of Management History*, 12(2), 185-198.

Goswami, O. (2002). Corporate governance in India. Taking action against corruption in Asia and the Pacific. In Proceedings of the 8th European Conference on Management Leadership and Governance. Academic Publishing International Limited, Reading, UK, 85-106.

Hillier, D., & McColgan, P. (2006). An analysis of changes in board structure during corporate governance reforms. *European Financial Management*, 12(4), 575-607.

Hillman, A. J., & Dalziel, T. 2003. Board of directors and firm performance: Integrating agency and resource dependence perspectives. *Academy of Management Review*, 28, 383-396.

Huggins, R. 2010. Forms of network resource: Knowledge access and the role of inter-firm networks. *International Journal of Management Reviews*, 12(3), 335-352.

Ingley, C., Khlif, W., & Karoui, L. 2017. SME growth trajectories, transitions and board role portfolios: A critical review and integrative model. *International Small Business Journal*, 35(6): 729-750.

Jackling, B., & Johl, S. 2009. Board structure and firm performance: Evidence from India's top companies. *Corporate Governance: An International Review*, 17(4), 492-509.

Joshi, M., Seidel-Morgenstern, A., & Kremling, A. (2006). Exploiting the bootstrap method for quantifying parameter confidence intervals in dynamical systems. *Metabolic Firming*, 8(5), 447-455.

Kapoor, R. 2014. Collaborating with complementors: What do firms do? In R. Adner, J. E. Oxley, & B. S. Silverman (Eds.). *Collaboration and Competition in Business Ecosystems* (Advances in Strategic Management, 30), 3-25. Emerald Group Publishing Limited.

Khanna, T., & Palepu, K. 2000. Is group affiliation profitable in emerging markets? An analysis of diversified Indian business groups. *Journal of Finance*, 55(2), 867-891.

Khanna, T., & Rivkin, J. W. 2001. Estimating the performance effects of business groups in emerging markets. *Strategic Management Journal*, 22(1), 45-74.

Klapper, L. F., & Love, I. 2004. Corporate governance, investor protection, and performance in emerging markets. *Journal of Corporate Finance*, 10(5), 703-728.

Kumar, N., & Singh, J. P. 2013. Effect of board size and promoter ownership on firm value: Some empirical findings from India. *Corporate Governance: International Journal of Business in Society*, 13: 88-98.

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (1999). Corporate ownership around the world. *Journal of Finance*, 54(2). 471-517.

Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science*, 43(4), 546-558.

Li, J-S., & Zhang, X-D. (1998). On the Laplacian eigenvalues of a graph. *Linear Algebra and its Applications*, 285(1–3), 305-307.

Manos, R., Murinde, V., & Green, C. J. 2007. Leverage and business groups: Evidence from Indian firms. *Journal of Economics and Business*, 59(5), 443-465.

Martin, G. P., Gomez-Mejia, Luis R., & Wiseman, R. M. (2013). Executive stock options as mixed gambles: Revisiting the behavioral agency model. *Academy of Management Journal*, 56(2), 451-472.

McDonald, M. L., Westphal, J. D., & Graebner, M. E. 2008. What do they know? The effects of outside director acquisition experience on firm acquisition performance. *Strategic Management Journal*, 29, 1155-1177.

Miller, D., Le Breton-Miller, I., & Scholnick, B. (2008). Stewardship vs. stagnation: An empirical comparison of small family and non-family businesses. *Journal of Management Studies*, 45(1), 51-78.

Mooney, C. Z., & Duval, R. D., 1993. *Bootstrapping: A Nonparametric Approach to Statistical Inference*. Sage Publications, Newbury Park, CA.

Newman, M. E. J. (2003). The Structure and Function of Complex Networks. *SIAM Review* 45(2), 167-256.

Newman, M. E. J. (2010). *Networks: An Introduction*. Oxford University Press, NY.

Nise, N. S. (2015). Control Systems Engineering. Wiley, NY.

Olfati-Saber, R. (2006). Flocking for multi-agent dynamic systems: algorithms and theory. *IEEE Transactions on Automatic Control*, 51(3), 401-420.

Parmigiani, A. & Mitchell, W. 2009. Complementarity, capabilities, and the boundaries of the firm: The impact of within-firm and interfirm expertise on concurrent sourcing of complementary components. *Strategic Management Journal*, 30(10), 1065-1091.

Paulraj, A., Lado, A. A., & Chen, I. J. 2008. Inter-organizational communication as a relational competency: Antecedents and performance outcomes in collaborative buyer–supplier relationships. *Journal of Operations Management*, 26(1), 45-64.

Pfeffer, J., & Salancik, G. R. 1978. *The External Control of Organizations: A Resource Dependence Perspective*. New York: Harper & Row.

Press, W. H., Teukolsky, S. A., Vetterling, W. T., Flannery, B. P. 1992. *Numerical Recipes in C. The Art of Scientific Computing*. Cambridge University Press, NY.

Litz, R. A. 1995. The family business: Toward definitional clarity. *Family Business Review*, 8(2), 71-81.

Ray, S., Mondal, A., & Ramachandran, K. 2018. How does family involvement affect a firm's internationalization? An investigation of Indian family firms. *Global Strategy Journal*, 8, 73-105.

Randolph, R.V., Fang, H.C., Memili, E., & Nayir, D.Z. 2021. Family and non-family sources of knowledge diversity in family firms: The role of causation logics. *International Small Business Journal*, 39(1): 64-85.

Rungtusanatham, M., Salvador, F., Forza, C., & Choi, T. Y. 2003. Supply-chain linkages and operational performance: A resource-based-view perspective. *International Journal of Operations & Production Management*, 23(9), 1084-1099.

Selarka, E. 2005. Ownership concentration and firm value: A study from the Indian corporate sector. *Emerging Markets Finance and Trade*, 41(6), 83-108.

Sankar, C. P., Asokan, K., & Kumar, K. S. 2015. Exploratory social network analysis of affiliation networks of Indian listed companies. *Social Networks*, 43, 113-120.

Short, H. (1994). Ownership, control, financial structure and the performance of firms. *Journal of Economic Surveys*, 8(3), 203-249.

Simpson, W. G., & Gleason, A. E. (1999). Board structure, ownership, and financial distress in banking firms. *International Review of Economics & Finance*, 8(3), 281-292.

Singla, C., Veliyath, R., & George, R. 2014. Family firms and internationalization-governance relationships: Evidence of secondary agency issues. *Strategic Management Journal*, 35(4), 606-616.

Thomas, D. J., & Griffin, P. M. (1996). Coordinated supply chain management. *European Journal of Operational Research*, 94(1), 1-15.

Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. *Journal of Finance*, 43(1), 1-19.

Villalonga, B., & Amit, R. 2006. How do family ownership, management, and control affect firm value? *Journal of Financial Economics*, 80, 385-417.

Wasserman, S., & Faust, K. (1994). *Social Network Analysis*. Cambridge, UK: Cambridge University Press.

Watts, D. J. 1999. Networks, dynamics, and the small-world phenomenon. *American Journal of Sociology*, 105(2), 493-527.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. *Nature*, 393, 440–442.

Westhead, P., Cowling, M., & Howorth, C. (2001). The development of family companies: Management and ownership imperatives. *Family Business Review*, 14(4), 369-385.

Young, M.N., Tsai, T., Wang, X., Liu, X., & Ahlstrom, D. (2014). Strategy in emerging economies and the theory of the firm. Asia Pacific Journal of Management 31(2), 331-354.

Zahra, S. A., & Pearce, J. A. II. 1989. Boards of directors and corporate financial performance: A review and integrative model. *Journal of Management*, 15, 291-334.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

AN ANOMALY WITHIN AN ANOMALY: THE HALLOWEEN EFFECT IN THE LONG-TERM REVERSAL ANOMALY

King Fuei Lee[1*]

1. Schroder Investment Management, Singapore

* Corresponding Author: Lee King Fuei, Co-Head of Asian Equity Alternative Investments, Schroder Investment Management, Singapore 048946, Tel: (+65) 6800 7000, ✉ Email: king.lee@schroders.com

Abstract

In this study, we investigated the presence of the Halloween effect in the long-term reversal anomaly in the US. After examining the cross-sectional returns of losers-minus-winners portfolios formed on prior returns over the period of 1931–2021, we found evidence of stronger returns during winter months versus summer months. Specifically, the effect appeared to be driven by a significant winter-summer seasonality in the portfolio of small-capitalisation losers and a lack of the Halloween effect in the portfolio of large-capitalisation winners. This study's results were found to be robust with respect to alternative measures of the long-term reversal effect, differing sub-periods, the inclusion of the January effect and outlier considerations, as well as regarding small- and large-sized companies.

Keywords: Halloween effect, Sell-in-May, long-term reversal, market anomaly

1. Introduction

The efficient market hypothesis (EMH) is one of the most influential theories in modern financial history. It is primarily attributed to Fama (1970), who posited that it is impossible to beat the market consistently on a risk-adjusted basis since asset prices reflect all available public information. Since his seminal work, many studies have unearthed and investigated market anomalies, which are essentially time-series or cross-sectional patterns in security returns that defy the rules of the EMH.

Over the past two decades, the Halloween effect, one of the most prominent seasonal market anomalies, has confounded market participants. This is also known as the 'Sell in May and go away' puzzle. Originally a part of a longer adage, 'Sell in May and go away, but buy back on St Leger's Day', this saying is believed to have originated in the period when City of London stockbrokers would escape their desks to enjoy the hot summer season that included many sporting and social festivities. With a paucity of market participants, the month of May thus heralds the beginning of a period of lacklustre market returns such that investors find it more rewarding to simply sell their stocks and hold cash. However, as St Leger's Day approaches in mid-September, investors are advised to re-enter stock markets in anticipation of a period of strong returns over the winter months. A pioneering study investigating the existence of a seasonal effect based on this old market adage was conducted by Bouman and Jacobsen (2002), who examined 37 developed and emerging markets over the period from January 1970 to August 1998 and found that the winter returns (November to April) were substantially higher than the summer returns (May to October) in 36 of these countries. According to them, this Halloween anomaly cannot be explained by data mining, the January effect, risk, sector-specific factors, news provision, or shifts in interest rates or trading volume. In an updated and extended form of this work, Zhang and Jacobsen (2021) investigated the Halloween effect from September 1998 to November 2011 by using the same 37 countries in Bouman and Jacobsen (2002) and found evidence of the continued presence of the Halloween effect in all of these countries, with 15 of them displaying statistically significant estimates. They also extended their analysis to 109 stock markets using a combined period spanning 323 years and found the mean returns from November–April to be higher than the mean returns from May–October in 82 of these countries. Their finding is interesting, because contrary to the predictions of the EMH and Schwert (2002), it seems that the 'Sell in May' anomaly has not been arbitraged away by rational investors even after the effect has been documented and publicised.

The prevalence of the Halloween effect is not only restricted to the national stock market indices. Arendas (2017) analysed 20 major agricultural commodities from 1980 to 2015, and found that 15 out of the 20 commodities, including corn, cotton, palm oil, and soybean, recorded higher average mean winter returns than summer returns. Burakov et al. (2018) performed a similar analysis on the energy markets over the period of 1985–2016 and found statistically significantly higher winter returns in the majority of these markets. Additionally, many studies have been conducted on the Halloween effect in the cross-sections of stock returns of numerous stock markets. For example, Jacobsen and Visaltanachoti (2009) examined sectors and industries within the US stock market during 1926–2006 and observed that 48 out of the 49 industries investigated performed better during the winter months as compared to the summer months, with two-thirds of these industries showing a statistically significant Halloween effect. On the other hand, Jacobsen et al. (2005) analysed US portfolios formed on size, dividend yield, book-to-market, earnings yield, and cash flow yield. They found that all the portfolios in their study showed higher mean winter returns and confirmed that the Halloween effect is a market-wide phenomenon.

In addition to the Halloween effect, another set of anomalies that have baffled EMH proponents are stock return anomalies, including the long-standing phenomenon, the long-term reversal effect. Originally hinted at by Jegadeesh and Titman (1993), who highlighted the U-shape of momentum returns across lengthening holding periods, the long-term reversal anomaly was formally introduced in the academic field by De Bondt and Thaler (1985), and it has since been confirmed by various studies, including Grinblatt and Moskowitz (2004) and Zaremba et al. (2020). Specifically, the long-term reversal anomaly refers to the tendency of stocks with low returns over the past 3–5 years to outperform stocks with high returns over the same time period. When De Bondt and Thaler (1985) examined the Center for Research in Security Prices (CRSP) monthly return data, they found that losers tended to earn approximately 25% more than winners 3 years after portfolio formation, despite the winners being significantly riskier. According to them, this phenomenon is consistent with the predictions of the overreaction hypothesis where individuals, in contradiction to Bayes' rule, 'overreact' to unexpected and dramatic news events in the short run, and subsequently correct for that overreaction in the long run. However, George and Hwang (2007) contested that the long-term reversal anomaly has more to do with tax loss harvesting than investor overreaction. In their view, as investors, due to the capital gains lock-in effect, have an incentive to delay selling their winners to avoid paying capital gains taxes, they demand higher reserve prices for the sale of these winners, which leads to winners having lower expected returns as compared to losers. Several other theoretical explanations for the existence of the anomaly have also been offered by researchers, including Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999). Regardless of the reasons for the long-term reversal effect, it is clear that the outperformance of losers versus winners in the long run remains a puzzle that intrigues researchers.

In recent years, a stream of research has emerged that investigates the Halloween anomaly within stock return anomalies. For instance, Fiore and Saha (2015) examined the seasonality of stock returns in low beta (low volatility) stocks and found that the low-risk anomaly appears only in summer months. Auer (2019) expanded on their work and investigated the winter-summer seasonality in other capital market anomalies of size, value, and momentum and beta in 21 developed stock markets. He found that the returns for the size and value (momentum and beta) anomalies tended to be higher in winter (summer) but pointed out that the results did not withstand statistical testing.

Therefore, our study adds to this growing stream of research by empirically investigating the seasonal Halloween effect in the long-term reversal anomaly. We found that the factor of mean monthly winter returns for the long-term reversal factor is statistically significantly higher than the mean monthly summer returns by 0.599%. Specifically, the Halloween effect appeared to be strongest in the extremely long portfolio consisting of small-capitalisation losers, and non-existent in the short portfolio comprising large-capitalisation winners. The other long portfolio including large-capitalisation losers and short portfolio including small-capitalisation winners showed a similar Halloween effect. We also conducted several robustness checks. These included employing alternative measures of the long-term reversal factor, accounting for the January and outlier effects, considering the firm size effect, in addition to conducting a sub-period analysis. We found that the winter-summer seasonality of long-term reversal returns is robust with respect to all these considerations. Specifically, consistent with Zhang and Jacobsen (2021), this Halloween effect appears to have been highly significant since the 1960s.

The motivations for our study were twofold. First, while a few studies have examined the Halloween effect in the size, value, momentum and beta, and low-volatility anomalies (Auer, 2019; Fiore and Saha, 2015), to our knowledge, no study has explored this seasonality effect in the long-term reversal anomaly. Therefore, our study fills this gap and contributes to the current literature. Second, our study increases the understanding of the long-term reversal effect and will be of particular interest to practitioners and investors seeking to exploit this market anomaly. Specifically, our finding regarding the winter-summer seasonality in the long-term reversal anomaly indicates the potential of applying market timing when employing long-term reversal strategies to enhance the risk-return profile of these strategies.

Our paper is structured as follows: Section 2 discusses the data and regression model employed in the study. Section 3 presents the empirical findings and robustness checks. Finally, Section 4 concludes the paper.

2. Data Sample and Methodology

This section briefly discusses the data sources, definitions of variables, and the methodology used in this study.

Our study covered the sample period from January 1931 to May 2021, and the stock universe from which the portfolios were constructed included NYSE, AMEX and NASDAQ firms which had prior return data. Following Zaremba et al. (2020), we measured long-term reversal as the stock returns over the previous 5-year period, excluding the previous 1 year (from months *t-13* to *t-60*). At the end of each month *t*, stocks were categorised into six value-weighted portfolios formed on size (measured as market equity) and prior returns. These six portfolios essentially represent the intersections of the two portfolios formed on size and the three portfolios formed on prior returns. The monthly size breakpoint is the median NYSE market equity, while the monthly prior return breakpoints are the 30th and 70th NYSE percentiles.

Subsequently, the long-term reversal factor (LT_REV) was constructed as a market-neutral portfolio comprising the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios.

$$LT\_REV = \tfrac{1}{2}\,(Small\ Losers + Big\ Losers) - \tfrac{1}{2}\,(Small\ Winners + Big\ Winners) \tag{1}$$

To investigate the statistical significance of the Halloween effect in the long-term reversal factor, we adopted the regression model employed by Bouman and Jacobsen (2002) and Zhang and Jacobsen (2021):

$$r_t = \alpha + \beta Hal_t + \varepsilon_t \tag{2}$$

where r_t is the continuously compounded monthly returns and Hal_t is the Halloween dummy that takes the value of 1 if month *t* falls within the winter months of November through April, and 0 otherwise. Therefore, the regression coefficient β represents the difference between the average returns of the two 6-month periods of November–April and May–October. If it is statistically significantly positive, it is inferred that the Halloween effect is present.

All data used for our calculations were obtained from the website of Kenneth French[1].

3. Empirical Findings

Table 1 shows the main summary statistics of the long-term reversal factor. It is observed that over the entire sample period, the long-term reversal factor has delivered a statistically positive average monthly return of 0.288%, indicating the existence of an anomaly in the US market. This finding is consistent with that of De Bondt and Thaler (1985) and Zaremba et al. (2020), who documented the outperformance of long-term losers to long-term winners. Interestingly, when our sample was split into two 6-month periods of winter months (November to April) and summer months (May to October), we observe that while the mean monthly returns factor remains statistically significantly positive in winter, the mean returns factor in summer is not statistically different from zero. This indicates that the long-term reversal anomaly is only prevalent during the months of November to April and not during the rest of the year, suggesting the existence of the Halloween effect.

Table 1: Summary Statistics

	Whole period	Winter months: November–April	Summer months: May–October
Mean	0.288	0.586	-0.013
Standard error	3.454	3.511	3.372
t-statistic	2.743***	3.894***	-0.086
Maximum	36.450	36.450	32.990
Minimum	-14.070	-8.730	-14.070
Skewness	2.827	3.153	2.499
Kurtosis	27.177	28.943	25.415
No. of observations	1085	544	541

Note: This table provides the summary statistics of the long-term reversal factor which is constructed as a market-neutral portfolio comprising the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. *Long-term reversal* is measured as the stock returns over the 5-year period excluding the previous 1 year.

Subsequently, " the Halloween effect regression analysis was conducted. Column 1 of Table 3 shows the results of the regression, where a positive Halloween effect is observed at the 1% significance level. Therefore, this study's results confirm the existence of the Halloween effect in the long-term reversal anomaly.

To further investigate the source of this seasonal effect in the long-term reversal anomaly, we examined the four individual portfolios that constitute the overall long-term reversal effect in Equation (1). We can observe from Table 2 that three out of the four portfolios exhibit statistically positive Halloween effects, with the long portfolio *Small Losers* showing the strongest Halloween effect and the short portfolio *Big Winners* showing no signs of the winter-summer seasonality. It is interesting to note that the magnitudes of the regression coefficients and t-statistics of the long portfolio *Big Losers* and short portfolio *Small Winners* are similar. This indicates that much of the Halloween effect that is observed in the long-term reversal anomaly in this study is driven by the strength of the Halloween effect (or lack of) in the extreme long (short) portfolios.

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

Table 2: Halloween effect in the Loser and Winner Portfolios

		Size	
		Small	**Big**
Long-term reversal	Losers	1.473***	0.794***
		(4.821)	(2.598)
	Winners	0.783**	0.286
		(2.563)	(4.821)

Note: This table provides the results from the Halloween effect regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$ where r_t is the continuously compounded monthly returns. The dummy variable Hal_t takes on the value 1 if month t falls within the winter months of November–April and 0 otherwise. *Long-term reversal* is measured as the stock returns over the previous 5-year period excluding the previous 1 year, while *Size* is measured as the market capitalisation of the stocks. The results exhibited are derived from the regressions run on the portfolios formed on the intersections of *Size* and Long-term reversal. T-statistics are shown in parentheses and are based on the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. Significance levels: *** = 1%, ** = 5%, * = 10%.

3.1 Robustness Checks

To ensure that our results are robust, we performed a number of checks.

3.1.1 Alternative Definitions of the Long-Term Reversal Factor

In this study, we followed the conventional method employed in various studies, such as Fama and French (1993) and Carhart (1997) to construct the long-term reversal factor. This involved using value-weighted portfolios that are formed at the 30th and 70th percentile breakpoints to calculate losers minus winner returns. However, some papers have adopted different methods in constructing the anomaly factor. For example, George and Hwang (2007) and Zaremba et al. (2020) used equal-weighted portfolios to calculate long-term reversal factor returns. Meanwhile, other studies such as Stambaugh and Yuan (2016) and Lettau and Pelger (2018) formed winner and loser portfolios by using decile breakpoints instead of tertile breakpoints.

Table 3: Halloween effect in in Long-term Reversal and Robustness Checks

Dependent variable	Long-term reversal								
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
		Robustness checks							
Explanatory variables		**Equal-weighted portfolios**	**Decile portfolios**	**January + outliers**	**Small firms**	**Big firms**	**1931–1960**	**1961–1990**	**1991–2021**
Halloween effect dummy	0.599***	0.761***	1.301***	0.298**	0.690***	0.508**	0.294	0.872***	0.631**
	(3.195)	(3.704)	(3.617)	(2.240)	(3.872)	(2.166)	(0.693)	(3.246)	(2.065)
January effect dummy	-	-	-	1.520***	-	-	-	-	-
	-	-	-	(3.975)	-	-	-	-	-
Outlier dummy	-	-	-	8.570***	-	-	-	-	-
	-	-	-	(4.478)	-	-	-	-	-
Intercept	-0.013	0.054	-0.157	-0.187*	-0.012	-0.014	0.263	-0.161	-0.138
	(-0.084)	(0.346)	(-0.541)	(-1.839)	(-0.084)	(-0.072)	(0.675)	(-0.938)	(-0.721)
No. of observations	1085	1085	1085	1085	1085	1085	360	360	365

Note: This table provides the results from the Halloween effect regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$, where r_t is the continuously compounded monthly returns. The dummy variable Hal_t takes on the value 1 if month t falls within the winter months of November–April and 0 otherwise. The January effect dummy variable takes on the value of 1 if the month t falls on January and 0 otherwise. The Outlier dummy variable takes the value of 1 when the absolute value of the within-sample Z-score of the monthly returns is greater than 2.50. Long-term reversal is measured as the stock returns over the previous 5-year period excluding the previous 1 year. Columns (1) and (2) show the results when the long-term reversal factor is constructed using equal-weighted tertile portfolios, and value-weighted decile portfolios respectively. Column (4) shows the results when the January effect dummy and the Outlier dummy are included. Column (5) and (6) show the results for using only small-capitalisation and large-capitalisation firms respectively. Columns (7) – (9) shows the results over the specified time periods. T-statistics are shown in parentheses and are based on the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. Significance levels: *** = 1%, ** = 5%, * = 10%.

Therefore, we checked the robustness of our results by adopting alternative measures of the long-term reversal factor. This was accomplished in two ways. First, we recalculated the factor returns by using equal-weighted portfolios instead of value-weighted portfolios. The calculation followed the same form as in Equation (1). Thus, Column 2 of Table 3 shows the results of the Halloween effect regression on the equal-weighted long-term reversal factor. It is observed that the Halloween effect remains statistically positive. In the second test, we calculated the long-term reversal factor by using the bottom decile portfolio minus the top decile portfolio formed on prior returns. It is observed from Column 3 of Table 3 that the Halloween effect remains positive at 1% significance level. The magnitude of the Halloween dummy regression coefficient in this column is also considerably larger than that in Column 1, indicating a stronger Halloween effect in the long-term reversal factor when extreme portfolios are used to form the factor. This reinforces our earlier finding that extreme portfolios are responsible for driving much of the seasonal effect observed in the stock return anomaly and shows that our finding is robust with respect to alternative measures of the long-term reversal factor.

3.1.2 January Effect and Outliers

Maberly and Pierce (2005) contended that an analysis of the Halloween effect using equation (2) ignores two important influences: the January effect and the presence of outliers, which can dramatically impact the regression results.

Previous studies (Haugen and Lakonishok, 1988; Rozeff and Kinney, 1976) have found that stock returns tend to be unusually large in January. Specifically, when De Bondt and Thaler (1987), in the follow-up study to their 1985 study that reported the discovery of the long-term reversal anomaly, acknowledged that long-term reversals tend to display a very strong seasonal pattern, with losers typically showing significant reversals only in January. This strong seasonality of long-term reversals was similarly observed by Grinblatt and Moskowitz (2004), who documented strong January reversals for long-term losers. This poses a risk because the conventional definition of the winter period used in most studies includes the period from November to April. This period encompasses January, which therefore raises the possibility that observations of the Halloween effect might simply be largely driven by the anomalous January returns. Therefore, it is important to consider the impact of the January effect.

In addition to the January effect, Maberly and Pierce (2005) highlighted the potential of outliers to distort the results of any Halloween effect analysis. For example, when they studied the Halloween effect in the US market, they found that the low average returns observed during the summer months were predominantly driven by two outlier events: the Stock Market Crash of 1987, which occurred in October 1987, and the Long-Term Capital Management Fund Crisis, which occurred in August 1998. When they controlled for the impact of these outliers, the Halloween effect in the US market became statistically insignificant.

To control for the January effect as well as the impact of outliers, they proposed that the Halloween effect be investigated by using the following regression model:

$$r_t = \alpha + \beta_1 Hal_t + \beta_2 Jan_t + \beta_3 Outlier_t + \varepsilon_t \tag{3}$$

where Jan_t is the January effect dummy that takes the value of 1 if month t falls in January and 0 otherwise. The variable $Outlier_t$ is the outlier dummy, which takes the value of 1 when the absolute value of the within-sample Z-score of the monthly returns is greater than 2.50.

Following the methodology of Maberly and Pierce (2005), we performed regressions using Equation (3). Our results are demonstrated in Column 4 of Table 3, where it is observed that the Halloween effect in the long-term reversal anomaly remains statistically positive even when considerations for the January effect and outliers are included. This confirms that the Halloween effect remains prevalent in the mean returns of the long-term reversal anomaly, even when we control for the January effect and the impact of outliers.

3.1.3 Firm size Effect

According to Zarowin (1990), smaller companies have a greater tendency of becoming loser firms because losers, by definition, are firms that have lost market share to winners. In his study of US companies over the period from 1932 to 1977, he found that the average size of losers was smaller than the average size of winners in 13 of the 17 non-overlapping 3-year periods under examination, and that 'the averages of the quintile ranks for losers and winners [also] show that losers tend to be among the smaller firms, while winners tend to be among the larger ones'. Thus, he posited that much of the reversal phenomenon documented by De Bondt and Thaler (1985) is essentially only the firm size effect.

The finding of Zarowin (1990) is interesting as it raises the possibility that the Halloween effect that we have found in the long-term reversal anomaly in this study is simply a reflection of the same Halloween effect that Auer (2019) identified in the size anomaly. To check the robustness of our findings, we controlled for the size effect by investigating the long-term reversal factor by using portfolios of firms of similar sizes. This is executed by separately calculating long-term reversal factors for small- and large-capitalisation firms:

$$LT\_REV_{Small} = Small\ Losers - Small\ Winners \tag{4}$$

$$LT\_REV_{Big} = Big\ Losers - Big\ Winners \tag{5}$$

Subsequently, we performed the Halloween effect regressions by using the two newly calculated factors. It is observed from Columns 5 and 6 of Table 3 that the Halloween effect in the long-term reversal anomaly within both small- and large-sized firms remains strongly positive. This indicates that the Halloween effect observed in the reversal phenomenon is not driven by the firm size effect.

3.1.4 Sub-period Analysis

To examine whether our findings are consistent over time, we divided our sample period into three sub-samples of approximately 30 years each. These three sub-samples span the period from January 1931 to December 1960, January 1961 to December 1990, and January 1991 to May 2021.

Columns 7–9 of Table 3 show the results of the regressions. It is discerned that the Halloween effect was not observed in the long-term reversal anomaly during the period of 1930–1960. However, the seasonal effect becomes much more pronounced in the long-term reversal anomaly from 1961 onwards, with the winter months delivering mean returns +0.872% higher than during the summer months over the period of 1961–1990, and +0.631% higher over the period–of 1991–2021. Interestingly, our finding of a more prevalent Halloween effect only after 1960 is similar to that of Zhang and Jacobsen (2021), who examined 65 international markets over 323 years and concluded that the Halloween effect only became statistically significant in the last 50 years, starting from the 1960s. Therefore, this finding confirms the significant winter-summer seasonality in the long-term reversal effect in the last 60 years after 1960.

4. Conclusion

Since the EMH was first proposed by Fama (1970), many studies have focused on uncovering market anomalies that defy the EMH rules. Specifically, the seasonal Halloween effect and the long-term reversal effect both represent peculiar puzzles for EMH proponents.

The objective of our study was to investigate the presence of an anomaly within an anomaly, specifically, the existence of the Halloween effect within the long-term reversal phenomenon. Using US data from January 1931 to May 2021, we found evidence of the existence of the winter-summer seasonality effect in the long-term reversal anomaly. Our work also showed that the effect appears to be driven by the extreme portfolios used to construct the anomaly, and that the Halloween effect has persisted since the 1960s. Additionally, we conducted a number of robustness checks and found our results to be robust to alternative definitions of the long-term reversal effect, the inclusion of the January effect and outlier dummies, and while controlling for the firm size effect, in addition to a differing sub-period analysis.

Therefore, our study contributes to the current literature by filling the gap in existing research regarding the Halloween effect within stock return anomalies and will be of particular interest to practitioners who are looking to exploit the long-term reversal effect in stock returns.

References

Arendas, P. 2017. The Halloween Effect on the Agricultural Commodities Markets. Agricultural Economics 63 (10): 441-448.

Auer, B. 2019. Does the Strength of Capital Market Anomalies Exhibit Seasonal Patterns?. Journal of Economics and Finance 43 (1), 91-103.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A Model of Investor Sentiment. Journal of Financial Economics 49 (3): 307-343.

Bouman, S., and B. Jacobsen. 2002. The Halloween Indicator, "Sell in May and Go Away": Another Puzzle. American Economic Review 92 (5): 1618-1635.

Burakov, D., M. Freidin, and Y. Solovyev. 2018. The Halloween Effect on Energy Markets: An Empirical Study. International Journal of Energy Economics and Policy 8 (2): 121-126.

Carhart, M. 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52 (1): 57-82.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor Psychology and Security Market Under- and Overreactions. Journal of Finance 53 (6), 1839-1885.

De Bondt, W., and R. Thaler. 1985. Does the Stock Market Overreact?. Journal of Finance 40 (3): 793-805.

De Bondt, W., and R. Thaler. 1987. Further Evidence on Investor Overreaction and Stock Market Seasonality. Journal of Finance 42 (3): 557-581.

Fama, E., and K. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33 (1): 3-56.

Fiore, C., and A. Saha. 2015. A Tale of Two Anomalies: Higher Returns of Low-Risk Stocks and Return Seasonality. Financial Review 50 (2): 257-273.

George, T., and C.Y. Hwang. 2007. Long-Term Return Reversals: Overreaction or Taxes?. Journal of Finance 62 (6): 2865-2896.

Grinblatt, M., and T. Moskowitz. 2004. Predicting Stock Price Movements from Past Returns: The Role of Consistency and Tax Loss Selling. Journal of Financial Economics 71 (3): 541-579.

Haugen, R.A., and J. Lakonishok. 1988. The Incredible January Effect: The Stock

Hong, H., and J. C. Stein. 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. Journal of Finance 54 (6): 2143-2184.

Jacobsen, B., A. Mamun, and N. Visaltanachoti. 2005. Seasonal, Size and Value Anomalies. Massey University Department of Commerce Working Paper Series Issue 5.

Jacobsen, B., and N. Visaltanachoti. 2009. The Halloween Effect in U.S. Sectors. Financial Review 44 (3): 437-459.

Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance 48 (1): 65-91.

Lettau, M., and N. Pelger. 2018. Factors that Fit the Time Series and Cross-Section of Stock Returns. National Bureau of Economic Research Working Paper No. 24858.

Maberly, E., and R. Pierce. 2005. The Halloween Effect and Japanese Equity Prices: Myth or Exploitable Anomaly. Asia-Pacific Financial Markets 10 (4): 319-334.

Rozeff, M., and W. Kinney. 1976. Capital Market Seasonality: The Case of Stock Returns. Journal of Financial Economics 3 (4): 379-402.

Schwert, W.G. 2002. Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of Economics and Finance. Amsterdam, Netherlands: North-Holland.

Stambaugh, R., and Y. Yuan. 2016. Mispricing Factors. Review of Financial Studies 30 (4): 1270-1315.

Zaremba, A., R. Kizys, and M.W. Raza. 2020. The Long-Run Reversal in the Long Run: Insights from Two Centuries of International Equity Returns. Journal of Empirical Finance 55 (C): 177-199.

Zarowin, P. 1990. Size, Seasonality and Stock Market Overreaction. Journal of Financial and Quantitative Analysis 25 (1): 113-125.

Zhang, C., and B. Jacobsen. 2021. The Halloween Indicator, “Sell in May and Go Away”: Everywhere and All the Time. Journal of International Money and Finance 110 (C): 1-49.

APPLIED FINANCE LETTERS

VOLUME 10, 2021

COST OF EQUITY CAPITAL AND UNDERSTATED PENSION LIABILITIES[1]

Huan Yang[1], Jun Cai[2], Lin Huang[1], and Robert I. Webb[3*]

1. Southwestern University of Finance and Economics
2. City University of Hong Kong
3. University of Virginia

* Corresponding Author: Robert I. Webb, McIntire School of Commerce, University of Virginia, Charlottesville, VA, USA, ✉ Email: riw4j@virginia.edu

Abstract
Pension discount rates have a powerful effect on the size of reported defined benefit corporate pension liabilities because of the long-term nature of projected benefit obligations. Firms often choose pension discount rates that are above the guideline long-term Treasury, AAA-grade, and AA-grade corporate bond yields. We assess the sizes of understated pension liabilities relative to these benchmark interest rates and relate them to individual firms' implied cost of equity. We find that firms with large, understated pension liabilities have a higher implied cost of equity after taking into account standard control variables and other pension information such as funded status and mandatory contributions.

Keywords: Cost of equity, pension discount rates, understated pension liabilities

1. Introduction

The cost of equity is one of the most important factors firms consider when making investment and financing decisions. A number of papers study alternative measures of cost of equity and relate them to beta, idiosyncratic volatility, size, book-to-market ratio, leverage, and growth expectations (see Botosan and Plumlee [2005]; Francis et al., [2004, 2005]), among many other variables.[2, 3] One common feature of these early studies is that they are based on either stock market information or reported financial statements or a combination of the two. In this paper, we examine the role of pension information. Unlike earnings-based information, pension information is primarily disclosed in notes to the financial statements rather than recognized in the financial statements themselves. Pension accounting also involves a complex smoothing procedure and the rules governing pension accounting keep changing over time. Even for sophisticated investors and analysts, the implication of pension information on firm valuation is difficult to process (Picconi [2006]).

We consider three measures of pension information: *funded status*, *mandatory contributions*, and *understated pension liabilities*. Understated pension liabilities capture the difference between reported pension liabilities and liabilities discounted at alternative guideline interest rates set forth by pension governing bodies and financial reporting standards. While the effect of funded status and mandatory contributions on cost of equity has been analysed by Campbell, Dhaliwal, and Schwartz,

[1] City University of Hong Kong Strategic Grant (SRG 7008142) is gratefully acknowledged. All errors remain our own responsibility.

[2] See Bhattacharya, Daouk, and Welker [2003]; Botosan, Plumlee, and Xie [2004]; Ecker, Francis, Kim, Olsson, and Schipper [2006]; Verdi [2006]; Nichols [2006]; Core, Guay, and Verdi [2008]; Liu and Wysocki [2008]; McInnis (2010); and Ogneva [2012].

[3] Diamond and Verrecchia [1991], O'Hara [2003], Easley and O'Hara [2004], and Lambert, Leuz, and Verrecchia [2007] develop alternative models to examine the role of structure, quality, and disclosure of information affecting firms' cost of equity.

Jr. [2012], the effect of understated pension liabilities on the cost of equity has not yet been explored in the literature.

We choose to focus on understated pension liabilities because (i) pension obligations such as projected benefit obligations are large in magnitude and very sensitive to small changes in pension discount rates because, as with any long-term fixed income instrument, these future cash flows are long term in nature. A rule of thumb is that a 1% change in the discount rate will lead to a 10% to 15% change in the present values of future cash flows. (ii) There are benefits and costs associated with choosing a high or low pension discount rate (Feldstein and Morck, [1983]. (iii) It has been well established that defined benefit pension accounting allows for considerable managerial discretion (Bergstresser, Desai, and Rauh [2006]. Managers may use pension accounting to boost reported earnings if investors do not "pierce the veil" (Coronado and Sharpe, [2003].

The legislation governing the minimum funding requirement for defined benefit corporate pension plans is the Employee Retirement Income Security Act (ERISA) enacted in 1974. It specifies that the interest rate used to calculate the present value of a plan's liabilities "must be within a specified range above or below the weighted average of the interest rates on 30-year Treasury bonds for the previous four-year period." That range is normally 90% to 105% of the weighted average. For financial reporting purposes in calculating projected and accumulated benefit obligations, the Financial Accounting Standard Board (FASB) statement SFAS 87 suggests "employers may also look to rates of return on high-quality fixed-income investments."

In this paper, we aim to answer two questions. First, to what extent do firms choose their pension discount rates in order to understate their true pension liabilities? Second, do understated pension liabilities affect firms' cost of capital? By choosing a high pension discount rate, firms can hide some of their pension obligations. The issue is whether investors see through the hidden pension liabilities and adjust their valuation of the firm's stock and cost of equity.

Our paper is related to a few other studies (Black [1989]; Brown and Wilcox [2009]; Novy-Marx and Rauh [2009]; Lucas and Zeldes [2006 and 2009]; Andonov, Bauer, and Cremers [2013]). Novy-Marx and Rauh [2011] evaluate the economic magnitude of public state pension liabilities. Hann, Lu, and Subramanyam [2007] develop methods to obtain defined benefit pension parameters. Building on their methods, we replace firm specific pension discount rates with alternative interest rate benchmarks to measure understated pension liabilities.

We examine the implied cost of equity rather than realized future returns, as suggested by Elton [1999] and Leuz and Wysocki [2008]. Therefore, our work differs from the two studies (Franzoni and Marin [2006]; Picconi, [2006] that use realized returns.

Our major findings can be summarized as follows. First, for each of the 11,450 firm-year observations of pension discount rates, we find the corresponding benchmark interest rates from 30-year Treasury bonds, 20-year, and 25-year AAA-grade corporate bonds. We also construct a term-structure benchmark AAA-grade corporate bond yield to take into account duration difference in pension liabilities. The average pension discount rate is 6.43%, which is 1.01%, 0.80%, 0.83%, and 0.70% higher than these four benchmark yields, respectively. The majority, or 86.9%, 83.9%, 84.3%, and 80.8%, of the 11,450 firm-year observations are associated with pension discount rates higher than these four benchmark yields. Using the 30-year Treasury bond yield, and the aforementioned three AAA-grade corporate bond yields, the average *projected benefit obligations* (PBOs) are understated by $141 million, $121 milllion, $122 million, and $121 million, respectively. This is equivalent to 2.7%, 2.3%, 2.3%, and 2.3% of the fiscal-year-end market value, respectively. The average *accumulated benefit obligations* (ABOs) are understated by $125 million, $107 million, $107 million, and $108 million, equivalent to 2.4%, 2.0%, 2.1%, and 2.1% of the fiscal-year-end market value, respectively. Relative to AA-grade corporate bond yields, the average difference between firm pension discount rates and benchmark yields becomes much smaller, and the percentage of firm pension discount rates higher than benchmark yields is also much lower. As a result, understated pension liabilities also become much smaller.

Second, we find that there is a reliable negative relation between understated pension liabilities and cost of equity after controlling for firm characteristics. Since understated pension liabilities are measured in negative numbers, the negative regression coefficients imply that firms with large amounts of hidden pension obligations face high costs of equity. The estimated coefficients (*t*-statistic) on understated PBOs are -0.029 (-3.11), -0.032 (-2.91), -0.031 (-2.99), and -0.027 (-2.81), respectively, relative to 30-year Treasury bond, 20-year, 25-year, and term structure AAA-grade corporate bond yields. The association between the cost of equity and understated ABOs is even stronger. The estimated coefficients are -0.035 (-3.26), -0.038 (-3.05), -0.037 (-3.12), and -0.033 (-2.97), respectively.

Third, we address the endogeneity issue with respect to the significant negative relation between the cost of equity and understated pension liabilities documented thus far. The endogeneity issue exists because pension discount rates are decision variables individual firms can choose. We rely on two-stage (2SLS) and three-stage least squares (3SLS) instrumental variable analysis. We conclude that the causal direction is from understated pension liabilities to the cost of equity.

The rest of the paper proceeds in the following way. Section 2 describes the data sources and sample screening. Section 3 describes the models for deriving the implied cost of equity. Section 4 explains the control variables. Section 5 provides summary statistics. Section 6 examines pension discount rates in relation to interest rate benchmarks. Section 7 assesses the magnitude of understated PBOs and ABOs. Section 8 studies the impact of understated pension liabilities on the implied cost of equity. Section 9 investigates the endogeneity issue. Finally, Section 10 concludes the paper.

2. Data Sources, Sample Screening, and FASB Statements

2.1 Data Sources

The data for U.S. equity markets is from WRDS's CRSP and COMPUSTAT merge files. We obtain market capitalization, daily individual stock returns, and value-weighted market portfolio returns from CRSP. The annual accounting items and pension variables are from COMPUSTAT. One-year-ahead and two-years-ahead forecasts of earnings per share, long-term earnings growth rate forecasts, and shares outstanding are from IBES. The data for 30-year Treasury bond yields are from WRDS. The yields on AAA-grade and AA-grade corporate bond yields are from Barclays Bank PLC. We obtain 15, 20, 25, and 30-year yields and number of bonds used to calculate the yields for AAA-grade and AA-grade corporate bonds.[4]

2.2 Sample Construction

Our sample firms consist of all NYSE/AMEX/NASDAQ firms that appear in the CRSP/COMPUSAT files. We include all industrial firms but exclude financial firms with 4-digit SIC codes between 6000 and 6999. Furthermore, we require firms to have a one-year-ahead and a two-years-ahead earnings-per-share (EPS) forecast, actual earnings-per-share, and shares outstanding from IBES. The merged CRSP/COMPUSTAT/IBES files generate a total of 41,653 firm-year observations from 6,147 firms during our sample period from October 1988 to June 2013. The pension dataset from COMPUSTAT contains 21,422 firm-year observations with non-missing PAs and PBOs on 1,556 firms over the same period.[5] After merging these two datasets, we retain 13,089 firm-year observations. We further require estimated cost of equity be available for the four models we consider. This eliminates an additional

[4] During our sample period from 1988 to 2012, the average number of bonds constituting 15, 20, 25, and 30-year AAA-grade corporate bond yields are 60, 45, 47, and 15. The average number of bonds that constitute 15, 20, 25, and 30-year AA-grade corporate bond yields are 48, 39, 64, and 29. For shorter maturity AAA-grade and AA-grade bond yields, the number of bonds is much larger.

[5] The firm-year observations and number of firms with pension information are similar to those reported in Rauh [2006] and Picconi [2006].

700 firm-year observations. Finally, we delete 939 firm-year observations with missing explanatory variables. Our final sample consists of 11,450 firm-year observations from 1,217 firms.

3. Cost of Equity

3.1 Existing Models of the Cost of Equity

We employ the following four models from the literature to obtain estimates for implied cost of equity: Gebhardt, Lee, and Swaminathan [2001]; Claus and Thomas [2001]; Ohlson and Juettner-Nauroth [2005]; and Easton [2004]. All four models are consistent with Gordon's [1962] dividend growth model, with some important differences. The Gebhardt, Lee, and Swaminathan [2001] and Claus and Thomas [2001] models are special cases of the residual income model in which dividend payments each period are modeled as:

$$P_t = BE_t + \sum_{\tau=1}^{T} \frac{(FEPS_{t+\tau} - x \cdot BE_{t+\tau-1})}{(1+x)^{\tau}} + TV_T. \qquad (1)$$

where x denotes cost of equity, P_t is stock price per share, BE_t is expected book value of equity per share, and $FEPS_{t+\tau}$ is expected earnings per share. The main difference between the Gebhardt, Lee, and Swaminathan [2001] and Claus and Thomas [2001] models lies in the assumptions made in computing terminal value TV_T.

Easton [2004] and Ohlson and Juettner-Nauroth [2005] develop an alternative representation of the dividend growth model, or abnormal earnings growth model, as follows:

$$P_t = \frac{FEPS_t}{x} + \sum_{\tau=1}^{\infty} \frac{AGR_{t+\tau}}{x \cdot (1+x)^{\tau}}, \qquad (2)$$

where $AGR_{t+\tau}$ equals expected abnormal growth in earnings. The major difference between the Easton [2004] and Ohlson and Juettner-Nauroth [2005] models lies in the assumption regarding expected abnormal growth in earnings. The detailed formulae to obtain the implied cost of equity from these four models are provided in unreported Appendix I.

4. Control Variables

4.1 Firm Characteristics

We consider several firm specific characteristics in our cross-sectional analysis, including beta (*BETA*), time-trend adjusted residual standard deviation (*ASTD*), market value (*ME*), book-to-market ratio (*BM*), market leverage (*MLEV*), liquidity (*LIQ*), interest coverage (*INTCOV*), operating margin (*MARGIN*), earnings loss frequency (*LOSS*), transparency (*TRANS*), Ohlson's [1980] bankruptcy score (*OBS*), and long-term growth rate of earnings per share (*LGROW*). The details of market and accounting items used to construct the variables are in unreported Appendix I.

4.2 Industry Cost of Equity

The industry cost of equity *IND_COST* has an important effect on individual firms' cost of equity (Gebhardt, Lee, and Swaminathan [2001]; Gode and Mohanram [2003]). For each of the 11,450 firm-year observations in our final sample, we obtain the corresponding industry median cost of equity. The industry median is taken from all firms with pension data in the same industry as the sample firm. The forty-eight industry classification is based on Fama and French [1997].

4.3 Pension Variables

Pension plan related variables include plan assets (*PA*), projected benefit obligations (*PBO*), accumulated benefit obligations (*ABO*), funded status (*FS*), and Moody's measure of mandatory contributions (*MC*). The details of the construction of these variables using COMPUSTAT items are available upon request.

The two primary variables used to measure the financial health of pension plans are funded status and mandatory contributions. Funded status (*FS*) is the difference between plan assets (*PA*) and projected benefit obligations (*PBO*). Rauh [2006] computes mandatory funding requirements for individual pension plans within each firm based on IRS 5500 filings to the U.S. Labor Department. IRS 5500 forms usually release data with a significant lag.

Alternatively, Mathur, Jonas, and LaMonte [2006] and Campbell, Dhaliwal, and Schwartz Jr. [2012] use a simpler measure for mandatory pension contributions. Their method for determining mandatory pension contributions relies on publicly available accounting disclosures in 10-K reports. Specifically,

$$\begin{aligned} MC_{i,t} &= -(SC_{i,t} + (ABO_{i,t} - PA_{i,t})/30), & \quad & if\, PBO_{i,t} \geq PA_{i,t}\,, \\ &= 0\,, & & if\, PBO_{i,t} < PA_{i,t}\,, \end{aligned} \tag{3}$$

where the funding shortfall of *ABO–PA* is amortized over a 30-year period before 2006.

5. Summary Statistics

Table 1 provides summary statistics. We use *COST_GLS*, *COST_CT*, *COST_PE*, and *COST_OJ* to denote implied cost of equity obtained from the four models, respectively. *COST* is the simple average of the four individual measures of cost of equity. The simple average cost of equity *COST* has a mean of 10.23%. Panel B computes the pairwise correlations between these four measures of cost of equity. All of them are positive and highly significant.

Panel A of Table 1 also summarizes firm characteristics including *BETA*, *ASTD*, *ME*, *BM*, *MLEV*, *LIQ*, *INTCOV*, *MARGIN*, *LOSS*, *TRANS*, *OBS*, and *LGROW*. All of these variables have been winsorized at 1% and 99%. Panels B and C further report the correlations between these firm characteristics. Two pension variables *FS* and *MC* are of primary interest. Panel A shows that the average funded status is -1.77% of fiscal-year-end market value. The average mandatory contribution is -0.41% of fiscal-year-end market value. Panel C reports that the correlation between *FS* and *MC* is 0.70.

Table 1: Summary Statistics

Panel A: Summary Statistics		**25%**	**Median**	**Mean**	**75%**	**Std. Dev.**
Cost of Equity						
Cost of Equity (%), Mean of the Four Estimated Cost of Equity	*COST*	8.37	9.68	10.23	11.34	3.00
Cost of Equity (%), Gebhardt, Lee, and Swaminathan [2001]	*COST_GLS*	6.01	7.66	7.98	9.58	2.92
Cost of Equity (%), Claus and Thomas [2001]	*COST_CT*	7.76	9.01	9.68	10.50	4.25
Cost of Equity (%), Ohlson and Juettner-Nauroth [2005]	*COST_OJ*	9.47	10.95	11.53	12.90	3.19
Cost of Equity (%), Easton [2004]	*COST_PE*	9.12	10.79	11.74	13.35	4.16
Firm Characteristics						
Beta	*BETA*	0.54	0.87	0.92	1.26	0.54
Time-Trend Adjusted Residual Standard Deviation	*ASTD*	0.62	0.81	0.89	1.06	0.36
Market Value at June (billion US$)	*ME*	0.54	1.72	7.22	5.51	16.95
Book-to-Market Ratio	*BM*	0.31	0.49	0.57	0.75	0.35
Market Leverage	*MLEV*	0.08	0.22	0.35	0.47	0.42
Liquidity	*LIQ*	0.01	0.03	0.07	0.11	0.08
Interest Coverage	*INTCOV*	3.00	5.58	15.16	12.83	24.97
Operating Margin	*MARGIN*	0.10	0.15	0.18	0.22	0.10
Percentage of Net Income Loss Years Over the Past Three years	*LOSS*	0.00	0.00	0.08	0.00	0.19
Transparency Measure	*TRANS*	-0.05	-0.04	-0.04	-0.02	0.02
Ohlson's (1980) Bankruptcy Score	*OBS*	-2.41	-1.56	-1.61	-0.78	1.20
Expected Long-Term Earnings Growth Rate	*LGROW*	0.09	0.12	0.14	0.15	0.12
Industry Cost of Equity						
Mean of the Four Measures of Industry Cost of Equity (%)	*IND_COST*	9.22	10.13	10.28	11.14	1.71
Pension Variables						
Funded Status (%)	*FS*	-3.61	-0.95	-1.77	0.37	7.63
Mandatory Contribution (%)	*MC*	-0.57	-0.18	-0.41	0.00	0.61

Panel B: Pairwise Correlations between Cost of Equity	***COST_GLS***	***COST_CT***	***COST_OJ***	***COST_PE***
COST	0.65**	0.82**	0.92**	0.89**
COST_GLS		0.37**	0.44**	0.46**
COST_CT			0.68**	0.55**
COST_OJ				0.87**

Panel C: Pairwise Correlations between Cost of Equity, Firm Characteristics, and Pension Variables

	BETA	**ASTD**	**ME**	**BM**	**MLEV**	**LIQ**	**INTCOV**	**MARGIN**
COST	0.10**	0.33**	-0.18**	0.44**	0.31**	0.23**	-0.13**	-0.28**
BETA		0.35**	-0.03**	-0.10**	-0.09**	-0.34**	0.08**	-0.14**
ATD			-0.23**	0.05**	0.07**	0.10**	0.09**	-0.27**
ME				-0.21**	-0.15**	-0.23**	0.06**	0.24**
BM					0.58**	0.20**	-0.24**	-0.06**
MLEV						0.13**	-0.36**	0.02*
LIQ							-0.07**	-0.05**
INTCOV								0.09**

	LOSS	***TRANS***	***OBS***	***LGROW***	***IND_COST***	***FS***	***MC***
COST	0.24**	-0.15**	0.18**	0.54**	0.57**	-0.06**	-0.18**
LOSS		-0.19**	0.18**	0.22**	0.10**	-0.18**	-0.20**
TRANS			0.08**	-0.20**	-0.10**	0.02**	-0.04**
OBS				-0.02**	0.01	-0.13**	-0.26**
LGROW					0.26**	-0.06**	-0.04**
IND_COST						0.02*	-0.03**
FS							0.70**

Note: The sample covers 11,450 firm-year observations from 1,217 firms from October 1988 to June 2013. Panel A of the table provides summary statistics for variables that belong to the following categories: individual firms' cost of equity, firm characteristics, industry cost of equity, and pension variables. COST is the simple average of four individual measures of cost of equity (COST_GLS, COST_CT, COST_OJ, and COST_PE). For each firm-year observation, individual measures of cost of equity are estimated based on each of the following four models: Gebhardt, Lee, and Swaminathan [2001]*; Claus and Thomas* [2001]*; Ohlson and Juettner-Nauroth* [2005]*; and Easton* [2004]*. Firm characteristics include beta (BETA), time-trend adjusted residual standard deviations (ASTD),* *market value in June of each year (ME), book-to-market ratio (BM), market leverage (MLEV), liquidity (LIQ), interest coverage (INTCOV), operating margin (MARGIN), percentage of net income loss years over the past three years (LOSS), transparency measure (TRANS), Ohlson's (1980) bankruptcy score (OBS), and expected long-term earnings growth rate (LGROW). Industry cost of equity IND_COST is the simple average of the estimates from the four models (IND_COST_GLS, IND_COST_CT, IND_COST_OJ, and IND_COST_PE), where each estimate is the median value of individual firms' cost of equity from firms in the same industry during the fiscal year. The forty-eight industry classification is based on Fama and French* [1997]. *Pension variables include funded status (FS) and mandatory contributions (MC). Panels B and C report pairwise correlations. The definitions of the variables are provided in Appendix I. Market data including market value, daily stock returns, and value-weighted market returns are from CRSP. Accounting and pension data are from COMPUSTAT. Earnings forecast data are from I/B/E/S. ** indicates significance at the 5% level; * indicates significance at the 10% level.*

6. Pension Discount Rates and Interest Rate Benchmarks

Table 2 compares the pension discount rates assumed by firms with alternative interest rate benchmarks. For each of the 11,450 firm-year observations of pension discount rates, we find the corresponding yields on 30-year Treasury bonds, 20-year and 25-year AAA-grade corporate bonds, and 20-year and 25-year AA-grade corporate bonds.

Table 2: Pension Discount Rate, Treasury Bond Yield, and High-Grade Corporate Bond Yield

Panel A: Mean Percentage Difference in $r^{DISCOUNT} - r^{Benchmark}$	**Mean (%)**	**Median (%)**
$r^{DISCOUNT} - r^{TB30Y}$	1.01	1.12
$r^{DISCOUNT} - r^{AAA20Y}$	0.80	0.98
$r^{DISCOUNT} - r^{AAA25Y}$	0.83	0.96
$r^{DISCOUNT} - r^{AAATM}$	0.70	0.91
$r^{DISCOUNT} - r^{AA20Y}$	-0.34	-0.08
$r^{DISCOUNT} - r^{AA25Y}$	-0.24	0.02
$r^{DISCOUNT} - r^{AATM}$	-0.26	-0.01
Observations	11,450	11,450

Panel B: Percentage of Firm-Year Observations with $r^{DISCOUNT} > r^{Benchmark}$	
$r^{DISCOUNT} > r^{TB30Y}$	86.9 %
$r^{DISCOUNT} >$.	83.9 %
$r^{DISCOUNT} > r^{AAA25Y}$	84.3 %
$r^{DISCOUNT} > r^{AAATM}$	80.8 %
$r^{DISCOUNT} > r^{AA20Y}$	43.0 %
$r^{DISCOUNT} > r^{AA25Y}$	52.1 %
$r^{DISCOUNT} > r^{AATM}$	49.3 %
Observations	11,450

Note: The sample covers 11,450 firm-year observations from 1,217 firms from October 1988 to June 2013. Panel A summarizes the difference between the pension discount rate ($r^{DISCOUNT}$) and the alternative interest rate benchmarks including 30-year Treasury bond yields (r^{TB30Y}), 20-year and 25-year AAA-grade corporate bond yields (r^{AAA20Y} and r^{AAA25Y}). 20-year and 25-year AA-grade corporate bond yields (r^{AA20Y} and r^{AA25Y})and term structure AAA-grade and AA-grade corporate bond yields (r^{AAATM} and r^{AATM}). For each firm-year observation with a pension discount rate, a corresponding yield r^{TB30Y}, r^{AAA20Y}, r^{AAA25Y}, r^{AA20Y}, r^{AA25Y} is first matched. Then the mean and median statistics are calculated among all firm-year observations. Panel B reports the percentage of firm-year observations for which the pension discount rate is higher than the corresponding interest rate benchmarks. ** indicates significance at the 5% level; * indicates significance at the 10% level. Petersen (2009) one-dimension firm-clustered t-statistics are reported.

We construct term-structure AAA yields using the 15, 20, 25, and 30-year AAA yields based on our estimated value of number of years to retirement *N*. This procedure also applies to term-structure AA yields using the 15, 20, 25, and 30-year AA yields.

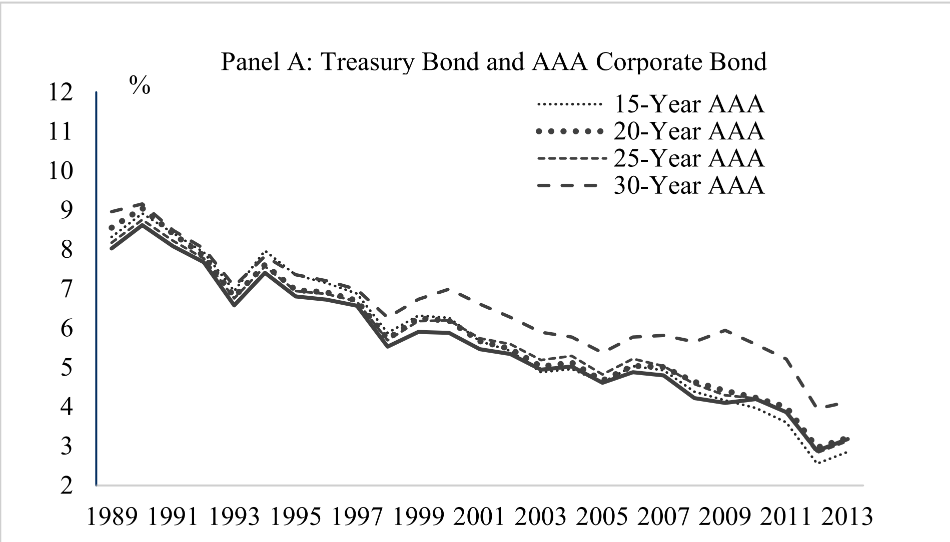
We calculate the average difference between pension discount rates and alternative interest rate benchmarks $r^{DISCOUNT} - r^{Benchmark}$ in Panel A of Table 2. The first column shows that given the average pension discount rate from the 11,450 firm-year observations was 6.43%, the average pension discount rate is 1.01%, 0.80%, 0.83%, and 0.70% higher than the average 30-year Treasury bond, 20-

year, 25-year, and term-structure AAA-grade corporate bond yields, respectively. The average difference becomes negative, or -0.34%, -0.24%, and -0.26%, respectively, relative to the 20-year, 25-year, and term-structure AA-grade corporate bond yields.

Panel B of Table 2 also summarizes the percentage of firm-year observations with pension discount rates larger than the corresponding interest rate benchmark. For example, Column 2 reports that 86.9% of the 11,450 pension discount rates are larger than the corresponding 30-year Treasury bond yields, while 83.9%, 84.3%, and 80.8% are larger than the 20-year, 25-year, and term-structure AAA-grade corporate bond yields, respectively. Therefore, the majority of the pension discount rates are above the long-term Treasury and AAA-grade corporate bond yields. In contrast, the percentages drop noticeably to 43.0%, 52.1%, and 49.3% relative to the long-term AA-grade benchmark yields.

We illustrate the evolution of pension discount rates and corresponding interest rate benchmarks for each year from 1989 to 2013 in Figure 2. The gap between pension discount rates and 30-year Treasury bond yields is the largest, followed by the gap between pension discount rates and long-term AAA-grade corporate bond yields. The gap seems to have not only persisted but also widened over time. On the other hand, the gap between pension discount rates and AA-grade corporate bond yields is much smaller.

Figure 1: Long-Term Treasury Bond and High-Grade Corporate Bond Yields



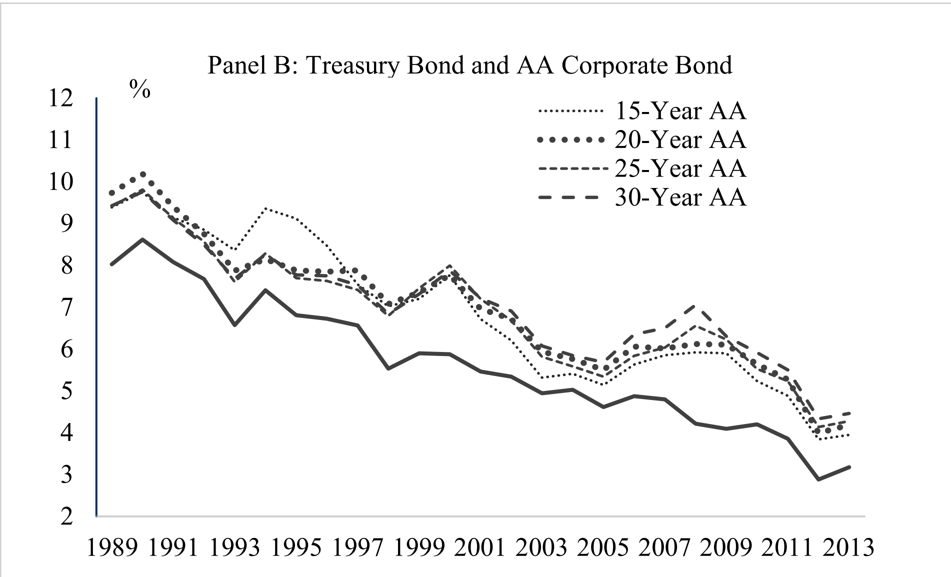
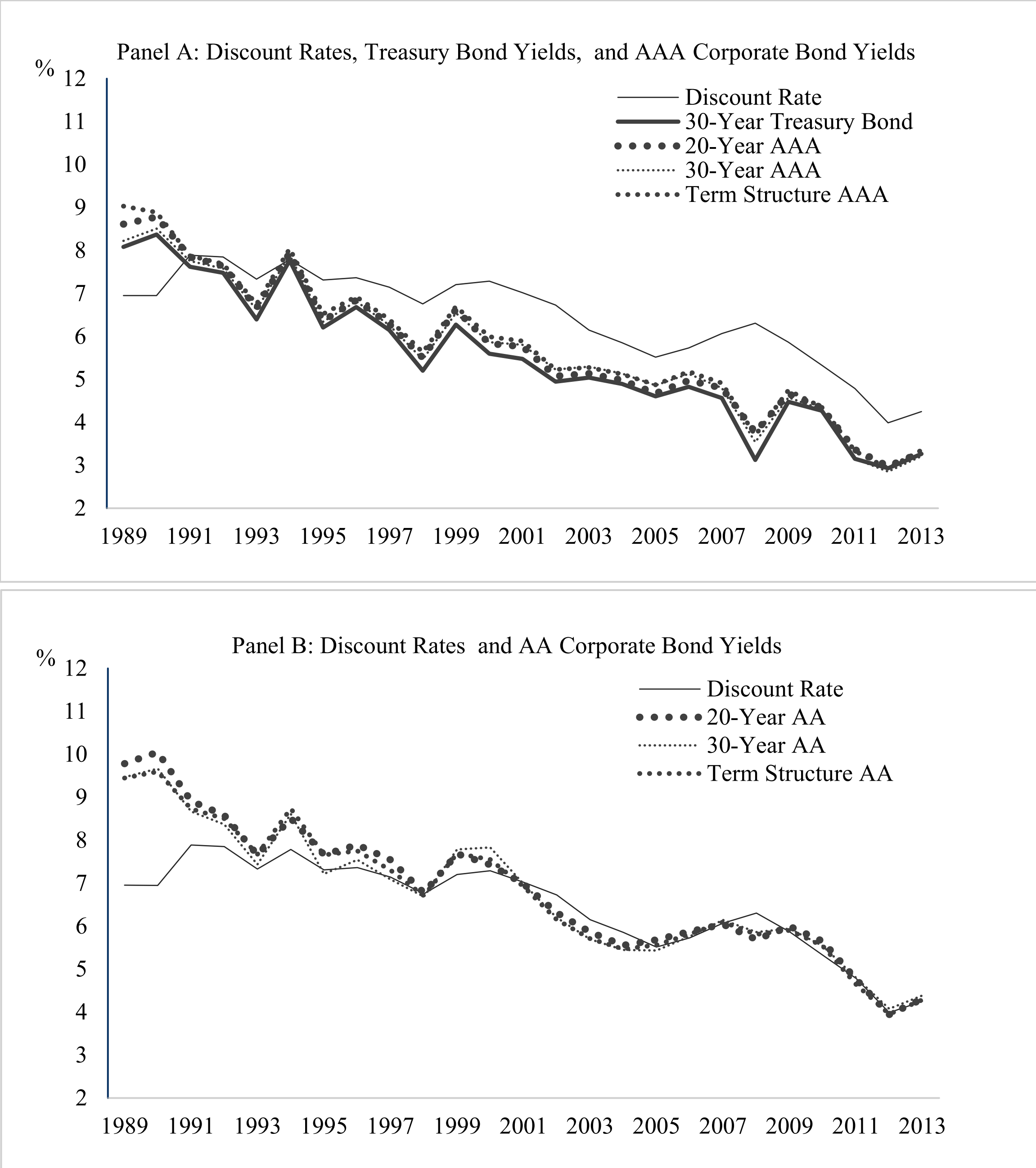


Figure 2: Pension Discount Rates and Interest Rate Benchmarks



7. Understated Pension Liabilities

7.1 Method for Computing Understated Pension Liabilities

The calculation of PBOs and ABOs for each individual employee requires firm level aggregate pension benefit formula parameters such as number of years to retirement (*N*), the percentage of current salary to be received after retirement (*K*), and current wages (*W*). We rely on the method developed in Hann, Lu, and Subramanyam [2007] to obtain these parameters at the aggregate firm level. Then we replace the assumed pension discount rate with alternative interest rate benchmarks to obtain the new PBO or ABO values. Notice that PBO is defined as:

$$PBO = \frac{A(r^{DISCOUNT}, L) \times K \times W \times (1+g)^N}{(1+r^{DISCOUNT})^N}, \tag{4}$$

where $A(r^{DISCOUNT}, L) = r^{-1}(1-(1+r^{DISCOUNT})^{-L})$ is the annuity factor of an *L* period annuity at a pension discount rate of $r^{DISCOUNT}$. *L* is the life expectancy of workers after retirement, *K* is the proportion of employees' wages that are payable given current service performed and vesting, *W, g,* and *N* denote current wage, compensation growth rate, and number of years to retirement, respectively. $K \times W \times (1+g)^N$ is the expected annuity the employee will receive after retirement. We make the assumption that the average life expectancy after retirement *L* is 15.[6] Then we need to estimate three parameters: *N*, *K*, and *W*. First, building on the relation between PBO and ABO:

$$PBO = ABO(1+g)^N, \tag{5}$$

then, we calculate *N* as:

$$\hat{N} = \log(PBO / ABO) / \log(1+g). \tag{6}$$

Now we can find the pension benefit formula parameters $\hat{K} \times \hat{W}$ as:

$$\hat{K} \times \hat{W} = \frac{PBO \times (1+r^{DISCOUNT})^{\hat{N}}}{A(r^{DISCOUNT}, \hat{L}) \times (1+g)^{\hat{N}}}. \tag{7}$$

As a result, PBO discounted at the 30-year Treasury bond yield can be calculated as:

$$PBO^{TB30Y} = \frac{A(r^{TB30Y}, \hat{L}) \times \hat{K} \times \hat{W} \times (1+g)^{\hat{N}}}{(1+r^{TB30Y})^{\hat{N}}}. \tag{8}$$

The understated PBO is the difference between the reported PBO and PBO^{TB30Y} divided by the fiscal year-end market value *ME*. For overstated PBOs, or PBO > PBO^{TB30Y}, we truncate their value at zero:

$$PCT\_TB30Y = \min\left(\frac{PBO - PBO^{TB30Y}}{ME},\ 0\right). \tag{9}$$

Similarly, ABO discounted at the 30-year Treasury bond yield can be computed as:

$$ABO^{TB30Y} = \frac{A(r^{TB30Y}, \hat{L}) \times \hat{K} \times \hat{W}}{(1+r^{TB30Y})^{\hat{N}}}. \tag{10}$$

The understated ABO is the difference between the reported ABO and ABO^{TB30Y} divided by the fiscal year-end market value *ME* truncated at a value of zero:

$$APCT\_TB30Y = \min\left(\frac{ABO - ABO^{TB30Y}}{ME},\ 0\right). \tag{11}$$

The truncation of *PCT_TB30Y* and *APCT_TB30Y* at a value of zero means that the largest value of these two measures is zero. Understated PBOs and ABOs relative to long-term AAA-grade and AA-grade corporate bond yields are calculated in an analogous way.

6 See the Centres for Medicare and Medicaid Services webpage: http://www.cms.hhs.gov.

7.2 How Much Do Firms Understate Their Pension Liabilities?

We obtain understated pension liabilities in dollar amounts and in percentages and summarize the results in Table 3. Panel A shows that the average of the understated PBOs is $141 million using r^{TB30Y} as the benchmark. The numbers become $121, $122, and $121 million, respectively, relative to the long-term AAA-grade corporate bond yields of r^{AAA20Y}, r^{AAA25Y}, and r^{AAATM}. When we scale the understated PBOs by fiscal-year-end market value, PBOs are understated by 2.7% relative to the Treasury benchmark and by 2.3%, 2.3%, and 2.3%, respectively, relative to three AAA-grade corporate bond yields. PBOs are understated by $17 million, $19 million, and $22 million, respectively, relative to the three AA-grade corporate bond yields. These translate into 0.4%, 0.4%, and 0.5% of the end of fiscal year market value.

Table 3: Summary Statistics

	5%	25%	Mean	Median	75%	95%
Benchmark	**Understated PBOs (million $)**					
r^{TB30Y}	-640.6	-82.7	-140.5	-16.3	-2.2	0.0
r^{AAA20Y}	-553.6	-70.4	-120.8	-13.4	-1.5	0.0
r^{AAA25Y}	-564.4	-70.6	-121.5	-13.0	-1.6	0.0
r^{AAATM}	-552.1	-65.5	-120.6	-11.0	-0.8	0.0
r^{AA20Y}	-84.7	-4.4	-16.9	0.0	0.0	0.0
r^{AA25Y}	-100.0	-6.6	-19.0	-0.1	0.0	0.0
r^{AATM}	-115.7	-6.7	-22.3	0.0	0.0	0.0
	Understated PBOs (%)					
r^{TB30Y}	-10.7	-3.2	-2.7	-1.2	-0.3	0.0
r^{AAA20Y}	-9.2	-2.8	-2.3	-1.0	-0.2	0.0
r^{AAA25Y}	-9.5	-2.8	-2.3	-1.0	-0.2	0.0
r^{AAATM}	-9.6	-2.7	-2.3	-0.9	-0.1	0.0
r^{AA20Y}	-2.0	-0.3	-0.4	0.0	0.0	0.0
r^{AA25Y}	-2.2	-0.4	-0.4	-0.1	0.0	0.0
r^{AATM}	-2.6	-0.4	-0.5	0.0	0.0	0.0
	Understated ABOs (million $)					
r^{TB30Y}	-572.4	-73.6	-124.7	-14.3	-1.8	0.0
r^{AAA20Y}	-493.9	-62.3	-106.8	-11.7	-1.3	0.0
r^{AAA25Y}	-508.6	-62.6	-107.4	-11.4	-1.3	0.0
r^{AAATM}	-499.9	-57.9	-107.6	-9.6	-0.7	0.0
r^{AA20Y}	-76.2	-3.8	-15.1	0.0	0.0	0.0
r^{AA25Y}	-88.9	-5.8	-16.9	-0.1	0.0	0.0
r^{AATM}	-104.2	-6.0	-19.9	0.0	0.0	0.0
	Understated ABOs (%)					
r^{TB30Y}	-9.5	-2.9	-2.4	-1.0	-0.2	0.0
r^{AAA20Y}	-8.2	-2.5	-2.0	-0.9	-0.2	0.0
r^{AAA25Y}	-8.5	-2.4	-2.1	-0.9	-0.2	0.0
r^{AAATM}	-8.6	-2.4	-2.1	-0.8	-0.1	0.0
r^{AA20Y}	-1.8	-0.2	-0.3	0.0	0.0	0.0
r^{AA25Y}	-2.0	-0.3	-0.4	-0.1	0.0	0.0
r^{AATM}	-2.4	-0.4	-0.4	0.0	0.0	0.0

Note: The sample covers 11,450 firm-year observations from 1,217 firms from October 1988 to June 2013. The table provides summary statistics for understated pension liability in dollar amounts and in percentages. The understated pension liabilities include projected benefit obligations (PBOs) and accumulated benefit obligations (ABOs) relative to the following interest rate benchmarks: r^{TB30Y}, r^{AAA20Y}, r^{AAA25Y}, r^{AAATM}, r^{AA20Y}, r^{AA25Y}, and r^{AATM}. The understated pension liabilities are scaled by fiscal-year-end market value. The discount factor assumes a life expectancy of 15 years from retirement age of 65. ** indicates significance at the 5% level; * indicates significance at the 10% level.

The patterns from understated ABOs essentially mirror those from PBOs. The average of the understated ABOs is $125 million using r^{TB30Y} as the benchmark. The numbers become $107 million,

\$107 million, and \$108 million, respectively, relative to the three AAA-grade corporate bond yields, r^{AAA20Y}, r^{AAA25Y}, and r^{AAATM}. As a percentage of fiscal-year-end market value, ABOs are understated by 2.4% relative to the Treasury benchmark and by 2.0%, 2.1%, and 2.1%, respectively, relative to the three AAA-grade corporate bond yield benchmarks. Relative to the AA-grade corporate bond yield benchmarks, ABOs are understated by \$15 million, \$17 million, and \$20 million, respectively. These hidden accumulated pension liabilities represent only 0.3%, 0.4%, and 0.4% of the market value corresponding to the fiscal year end.

8. Empirical Tests for the Determinants of Cost of Equity

We begin the empirical analysis by running the following OLS regressions. The model is specified with the cost of equity *COST*, the simple average of *COST_GLS*, *COST_CT*, *COST_PE*, and *COST_OJ*, as the dependent variable. The independent variables include firm characteristics and pension variables. We also include calendar year and industry dummies:

$$\begin{aligned} COST_{it+1} = {} & \alpha_0 + \alpha_1 BETA_{it} + \alpha_2 ASTD_{it} + \alpha_3 ME_{it} + \alpha_4 BM_{it} + \alpha_5 MLEV_{it} + \alpha_6 LIQ_{it} \\ & + \alpha_7 INTCOV_{it} + \alpha_8 MARGIN_{it} + \alpha_9 LOSS_{it} + \alpha_{10} TRANS_{it} + \alpha_{11} OBS_{it} \\ & + \alpha_{12} LGROW_{it} + \alpha_{13} IND\_COST_{it} + \alpha_{14} FS_{it} + \alpha_{15} MC_{it} + \alpha_{16} USPL_{it} + \\ & + \sum_{j=1}^{24} \lambda_j^{Year} D_j^{Year} + \sum_{k=1}^{43} \lambda_k^{Industry} D_k^{Industry}, \end{aligned} \tag{12}$$

where $USPL_{it}$ denotes understated PBOs and understated ABOs. We report the regression results for *UPBO*s and *UABO*s in Panels A and B of Table 4, respectively.

From Model 1 in Panel A, the estimated coefficient (*t*-statistic) on *PCT_TB30Y* is -0.029 (-3.11). Despite the strong correlation of 0.58 between *MC* and *PCT_TB30Y*, the understated pension liability has incremental explanatory power. The evidence provides strong support for our hypothesis that firms with more hidden pension liabilities face a higher cost of equity. The estimate is precise with a large t-statistic. Similarly, Panel A shows that when we replace *PCT_TB30Y* by *PCT_AAA20Y*, *PCT_AAA25Y*, and *PCT_AAATM* one at a time in the regression in Equation (12), the estimates (*t*-statistic) are -0.032 (-2.91), -0.031 (-2.99), and -0.027 (-2.81), respectively.

When understated ABOs are included in Equation (12) in Panel B, the estimates (*t*-statistic) on *APCT_TB30Y*, *APCT_AAA20Y*, *APCT_AAA25Y*, and *APCT_AAATM* are -0.035 (-3.26), -0.038 (-3.05), -0.037 (-3.12), and -0.033 (-2.97), respectively. Therefore, the empirical evidence from ABOs also provides strong support for our hypothesis that firms with more hidden pension liabilities face a higher cost of equity. Overall, the empirical results suggest that understated pension liabilities relative to 30-year Treasury bond and AAA-grade corporate bond yields significantly increase the cost of equity. This effect is incremental in the presence of other pension variables such as funded status and mandatory contributions. Similarly, all *t*-statistics have been adjusted for clustering-in-firm effects (Petersen, 2009).

Now we examine whether understated pension liabilities relative to AA-grade corporate bond yields also affect firms' cost of equity. We run the same regression as specified in Equation (12), where $USPL_{it}$ now denotes, for example, *PCT_AA20Y*. The empirical results appear in the last three columns of Panels A and B in Table 4. When measured relative to AA-grade corporate bond yields, understated pension liabilities become insignificantly related to individual firms' cost of equity.

Table 4: Implied Cost of Equity and Understated Pension Liabilities

Panel A: Understated PBOs Included							
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
BETA	0.122	0.121	0.121	0.120	0.121	0.120	0.119
	(2.04)**	(2.04)**	(2.04)**	(2.02)**	(2.04)**	(2.01)**	(2.01)**
ASTD	0.260	0.260	0.260	0.261	0.260	0.263	0.260
	(2.68)**	(2.69)**	(2.68)**	(2.69**	(2.67)**	(2.71)**	(2.68)**
ME	0.058	0.058	0.058	0.057	0.060	0.061	0.060
	(1.93)*	(1.94)*	(1.93)*	(1.92)*	(2.02)**	(2.03)**	(2.01)**
BM	3.093	3.096	3.095	3.096	3.114	3.117	3.114
	(21.73)**	(21.76)**	(21.73)**	(21.72)**	(21.85)**	(21.84)**	(21.87)**
MLEV	0.639	0.641	0.642	0.644	0.656	0.656	0.653
	(5.11)**	(5.12)**	(5.13)**	(5.13)**	(5.21)**	(5.20)**	(5.17)**
LIQ	3.159	3.160	3.156	3.159	3.166	3.139	3.155
	(4.95)**	(4.95)**	(4.95)**	(4.94)**	(4.94)**	(4.89)**	(4.92)**
INTCOV	0.002	0.001	0.001	0.001	0.002	0.002	0.002
	(1.29)	(1.30)	(1.30)	(1.30)	(1.34)	(1.35)	(1.34)
MARGIN	-1.645	-1.646	-1.650	-1.653	-1.688	-1.692	-1.687
	(-4.33)**	(-4.33)**	(-4.35)**	(-4.35)**	(-4.46)**	(-4.48)**	(-4.46)**
LOSS	0.049	0.050	0.051	0.050	0.052	0.049	0.051
	(0.32)	(0.33)	(0.34)	(0.33)	(0.34)	(0.32)	(0.34)
TRANS	-3.740	-3.745	-3.737	-3.746	-3.761	-3.749	-3.757
	(-3.20)**	(-3.20)**	(-3.20)**	(-3.20)**	(-3.21)**	(-3.20)**	(-3.21)**
OBS	0.226	0.227	0.227	0.227	0.236	0.237	0.235
	(6.03)**	(6.06)**	(6.05)**	(6.06)**	(6.27)**	(6.28)**	(6.27)**
LGROW	10.663	10.664	10.664	10.662	10.671	10.678	10.674
	(24.69)**	(24.68)**	(24.67)**	(24.66)**	(24.71)**	(24.71)**	(24.70)**
IND_COST	0.478	0.478	0.478	0.478	0.479	0.479	0.479
	(20.72)**	(20.71)**	(20.71)**	(20.70)**	(20.69)**	(20.70)**	(20.68)**
FS	0.020	0.020	0.020	0.021	0.021	0.020	0.021
	(3.60)**	(3.65)**	(3.68)**	(3.80)**	(3.69)**	(3.65)**	(3.73)**
MC	-0.309	-0.314	-0.318	-0.335	-0.373	-0.383	-0.384
	(-4.38)**	(-4.46)**	(-4.57)**	(-4.89)**	(-5.33)**	(-5.39)**	(-5.57)**
PCT_TB30Y	-0.029						
	(-3.11)**						
PCT_AAA20Y		-0.032					
		(-2.91)**					
PCT_AAA25Y			-0.031				
			(-2.99)**				
PCT_AAATM				-0.027			
				(-2.81)**			
PCT_AA20Y					-0.062		
					(-1.65)*		
PCT_AA25Y						-0.036	
						(-1.07)	
PCT_AATM							-0.042
							(-1.49)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.699	0.699	0.699	0.699	0.699	0.699	0.699
Observations	11,450	11,450	11,450	11,450	11,450	11,450	11,450

Panel B: Understated ABOs Included							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
BETA	0.120	0.120	0.120	0.119	0.122	0.120	0.119
	(2.03)**	(2.02)**	(2.03)**	(2.00)**	(2.04)**	(2.02)**	(2.00)**
ASTD	0.258	0.258	0.258	0.259	0.259	0.262	0.259
	(2.66)**	(2.67)**	(2.66)**	(2.67)**	(2.66)**	(2.70)**	(2.66)**
ME	0.056	0.057	0.057	0.056	0.060	0.060	0.060
	(1.89)*	(1.90)*	(1.89)*	(1.88)*	(2.01)**	(2.02)*	(2.00)*
BM	3.090	3.093	3.092	3.093	3.113	3.116	3.113
	(21.68)**	(21.70)**	(21.67)**	(21.67)**	(21.84)**	(21.83)**	(21.86)**
MLEV	0.637	0.639	0.641	0.643	0.655	0.656	0.653
	(5.09)**	(5.10)**	(5.12)**	(5.12)**	(5.20)**	(5.19)**	(5.16)**
LIQ	3.159	3.159	3.155	3.158	3.167	3.140	3.156
	(4.95)**	(4.95)**	(4.94)**	(4.94)**	(4.94)**	(4.90)**	(4.92)**
INTCOV	0.001	0.001	0.001	0.001	0.002	0.002	0.002
	(1.28)	(1.29)	(1.29)	(1.29)	(1.34)	(1.35)	(1.34)
MARGIN	-1.639	-1.642	-1.645	-1.647	-1.688	-1.691	-1.685
	(-4.32)**	(-4.33)**	(-4.34)**	(-4.34)**	(-4.46)**	(-4.48)**	(-4.46)**
LOSS	0.047	0.048	0.050	0.049	0.051	0.048	0.050
	(0.31)	(0.32)	(0.33)	(0.32)	(0.34)	(0.32)	(0.33)
TRANS	-3.757	-3.760	-3.751	-3.758	-3.768	-3.754	-3.764
	(-3.21)**	(-3.22)**	(-3.21)**	(-3.21)**	(-3.22)**	(-3.21)**	(-3.22)**
OBS	0.225	0.226	0.226	0.226	0.235	0.236	0.235
	(5.98)**	(6.02)**	(6.00)**	(6.02)**	(6.26)**	(6.27)**	(6.26)**
LGROW	10.662	10.662	10.663	10.660	10.669	10.678	10.673
	(24.68)**	(24.68)**	(24.66)**	(24.66)**	(24.71)**	(24.71)**	(24.70)**
IND_COST	0.478	0.478	0.478	0.478	0.479	0.479	0.478
	(20.72)**	(20.71)**	(20.71)**	(20.70)**	(20.68)**	(20.69)**	(20.68)**
FS	0.020	0.020	0.020	0.021	0.021	0.020	0.021
	(3.60)**	(3.66)**	(3.68)**	(3.82)**	(3.70)**	(3.65)**	(3.74)**
MC	-0.299	-0.306	-0.311	-0.328	-0.371	-0.380	-0.381
	(-4.20)**	(-4.30)**	(-4.42)**	(-4.76)**	(-5.28)**	(-5.33)**	(-5.53)**
APCT_TB30Y	-0.035						
	(-3.26)**						
APCT_AAA20Y		-0.038					
		(-3.05)**					
APCT_AAA25Y			-0.037				
			(-3.12)**				
APCT_AAATM				-0.033			
				(-2.97)**			
APCT_AA20Y					-0.074		
					(-1.72)*		
APCT_AA25Y						-0.046	
						(-1.20)	
APCT_AATM							-0.051
							(-1.60)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.700	0.699	0.699	0.699	0.699	0.699	0.699
Observations	11,450	11,450	11,450	11,450	11,450	11,450	11,450

Note: The sample covers 11,450 firm-year observations from 1,217 firms from October 1988 to June 2013. The table provides OLS regressions of individual firms' cost of equity (*COST*) on firm characteristics, industry cost of equity, pension variables, year dummies, and industry dummies. *COST* is the simple average of four individual measures of cost of equity, *COST_GLS*, *COST_CT*, *COST_OJ*, and *COST_PE*. Firm characteristics include *BETA*, *ASTD*, *ME*, *BM*, *MLEV*, *LIQ*, *INTCOV*, *MARGIN*, *LOSS*, *TRANS*,*OBS*, and *LGROW*. Industry cost of equity *IND_COST* is the simple average of the estimates from the four models (*IND_COST_GLS*, *IND_COST_CT*, *IND_COST_OJ*, and *IND_COST_PE*), where each estimate is the median value of individual firms' cost of equity from firms in the same industry during the fiscal year. The forty-eight industry classification is based on Fama and French [1997]. Pension variables include mandatory contributions (*MC*), understated PBOs (*PCT_TB30Y*, *PCT_AAA20Y*, *PCTAAA_30Y*, and *PCT_AAATM*), and understated ABOs (*APCT_TB30Y*, *APCT_AAA20Y*, *APCTAAA_30Y*, and *APCT_AAATM*). The definitions of the variables are provided in Appendix I. ** indicates significance at the 5% level; * indicates significance at the 10% level. Petersen [2009] one-dimension firm-clustered t-statistics are reported.

9. Instrumental Variable Analysis

In this section, we address the endogeneity issue with respect to the significant negative relation between the cost of equity and understated pension liabilities documented thus far. The endogeneity issue takes place because pension discount rates are *decision variables* individual firms can choose. Our hypothesis is that firms try to hide their pension liabilities, but equity markets detect firms' attempts and demand higher expected returns. The alternative hypothesis is that those firms facing a higher cost of equity try to hide more of their pension liabilities. We now specify a system of two equations for *COST* and *USPL* as follows:

$$COST_{i,t} = \beta_0 + \beta_1 USPL_{i,t} + Z_{i,t} \bullet \beta + \sum_{j=1}^{24} D_j^{Year} + \sum_{k=1}^{43} D_k^{Industry} + \varepsilon_{\mathrm{i,t}}, \qquad (13)$$

$$USPL_{i,t} = \gamma_0 + \gamma_1 COST_{i,t} + Z_{i,t} \bullet \gamma + \sum_{j=1}^{24} D_j^{Year} + \sum_{k=1}^{43} ID_k^{Industry} + \varepsilon_{\mathrm{i,t}}, \qquad (14)$$

where Z = [*BETA*, *ASTD*, *ME*, *BM*, *MLEV*, *LIQ*, *INTCOV*, *MARGIN*, *LOSS*, *TRANS*, *OBS*, *LGROW*, *IND_COST*, *TB1Y*, *FS*, *MC*] denotes a vector of 16 exogenous variables. *COST* measures the average cost of equity. *USPL* refers to understated PBOs (*PCT_TB30Y*, *PCT_AAA20Y*, *PCT_AAA25Y*, *PCT_AAATM*) and understated ABOs (*APCT_TB30Y*, *APCT_AAA20Y*, *APCT_AAA25Y*, *APCT_AAATM*), respectively. The two vectors of parameters to be estimated from the above system are $\beta = [\beta_2 ... \beta_{16}]'$ and $\gamma = [\gamma_2 ... \gamma_{16}]'$. We need to perform diagnostics and identify the strong instruments that can be used in predicting the two endogenous variables *COST* and *USPL*. Stock and Yogo (2002) and Stock, Wright, and Yogo (2002) suggest that the exogenous variable starts to qualify as a strong instrument at an *F*-statistic of 8.96. Based on the *F*-statistics, we confirm that *BM*, *MLEV*, *LIQ*, *MARGIN*, *TRANS*, *OBS*, *LGROW*, *IND_COST*, *FS*, and *MC* serve as strong instruments for *COST*. For all four measures of understated PBOs, *MARGIN*, *OBS*, *TB1Y*, and *MC* serve as strong instruments. Likewise, for all four measures of understated ABOs, the same set of variables serve as strong instruments.

In Table 5, we implement the two stage least squares (2SLS) analysis. In the 2SLS estimation, Equations *(13)* and *(14)* are estimated separately. In the equation that determines *COST*, the estimates (*t*-statistic) for four instrumented *UPBO*s are -0.126 (-5.57), -0.150 (-5.49), -0.151 (-5.47), and -0.172 (-5.29), respectively, from Models 1 to 4 in Panel A. The evidence provides strong support for our hypothesis that equity market investors detect managers' attempts to hide their pension obligations and adjust their required returns on firms' stocks accordingly. The over-identifying restrictions test statistics (*p*-value) are: 1.20 (0.55); 1.20 (0.55); 1.28 (0.53); and 1.20 (0.55), respectively. Therefore, we cannot reject the hypothesis that our model for *COST* is well specified.

On the other hand, in the equation that explains understated *PBO*s, the estimates for instrumented *COST* are not significant for all four measures of understated *PBO*s from Models 1 to 4 in Panel A. The implication is that cost of equity does not affect understated pension liabilities. Therefore, the evidence does not provide support for the alternative hypothesis that firms with higher cost of equity tend to hide more of their pension liabilities. The conclusion we derive that using understated *ABO*s to measure understated pension liabilities is essentially the same as using understated *PBO*s. [7, 8]

[7] The three stage least squares (3SLS) estimates are similar to 2SLS estimates in magnitude.

[8] We also estimate Equation (12) using four individual measures of implied cost of equity *COST_GLS*, *COST_CT*, *COST_OJ*, and *COST_PE* as the dependent variables. The results are similar.

Table 5: The Determinants of Implied Cost of Equity and Understated Pension Liabilities: 2SLS Analysis

Panel A: The Determinants of RATING and UPBOs								
	Model 1		Model 2		Model 3		Model 4	
	COST	*PCT_ TB30Y*	*COST*	*PCT_ _AAA20Y*	*COST*	*PCT_ _AAA25Y*	*COST*	*PCT_ _AAATM*
UPBOs (instrumented)	-0.126		-0.150		-0.151		-0.172	
	(-5.57)**		(-5.49)**		(-5.47)**		(-5.29)**	
COST (instrumented)		-0.056		-0.015		-0.040		-0.040
		(-0.76)		(-0.25)		(-0.61)		(-0.57)
BETA	0.127		0.125		0.126		0.123	
	(2.11)**		(2.08)**		(2.09)**		(2.01)**	
ASTD	0.266	-0.040	0.270	-0.031	0.267	-0.043	0.270	-0.030
	(2.75)**	(-0.22)	(2.78)**	(-0.20)	(2.74)**	(-0.26)	(2.74)**	(-0.16)
ME	0.047	-0.065	0.049	-0.041	0.047	-0.052	0.044	-0.073
	(1.64)	(-1.27)	(1.70)*	(-0.90)	(1.64)	(-1.12)	(1.50)	(-1.49)
BM	2.998	-0.626	3.012	-0.517	2.999	-0.541	2.988	-0.524
	(21.27)**	(-1.52)	(21.31)**	(-1.46)	(21.17)**	(-1.48)	(20.64)**	(-1.31)
LLEV	0.564	-0.788	0.567	-0.668	0.567	-0.655	0.558	-0.623
	(4.33)**	(-2.89)**	(4.35)**	(-2.83)**	(4.33)**	(-2.73)**	(4.14)**	(-2.33)**
LIQ	3.136		3.139		3.115		3.174	
	(4.87)*		(4.82)*		(4.80)*		(4.77)*	
INTCOV		-0.003		-0.002		-0.002		-0.002
		(-1.45)		(-1.07)		(-1.27)		(-1.12)
MARGIN	-1.434	1.983	-1.434	1.719	-1.437	1.665	-1.393	1.736
	(-3.66)**	(3.59)**	(-3.65)**	(3.57)**	(-3.66)**	(3.39)**	(-3.48)**	(3.22)**
LOSS		0.072		0.129		0.155		0.171
		(0.26)		(0.53)		(0.63)		(0.62)
TRANS	-3.769	0.092	-3.749	0.405	-3.740	0.363	-3.753	0.283
	(-3.23)**	(0.05)	(-3.21)**	(0.24)	(-3.20)**	(0.21)	(-3.16)**	(0.15)
OBS	0.180	-0.342	0.184	-0.260	0.180	-0.289	0.172	-0.300
	(5.30)**	(-4.63)**	(5.43)**	(-4.11)**	(5.28)**	(-4.42)**	(4.95)**	(-4.21)**
LGROW	10.593	-0.150	10.579	-0.562	10.581	-0.291	10.531	-0.500
	(24.57)**	(-0.14)	(24.49)**	(-0.60)	(24.39)**	(-0.30)	(24.03)**	(-0.47)
IND_	0.475		0.477		0.476		0.475	
	(20.61)**		(20.52)**		(20.51)**		(20.32)**	
TB1Y	0.125	0.696	0.123	0.569	0.130	0.615	0.142	0.608
	(3.50)**	(9.50)**	(3.44)**	(9.10)**	(3.58)**	(9.38)**	(3.73)**	(9.02)**
FS	0.019	-0.011	0.021	0.004	0.022	0.008	0.029	0.048
	(3.32)**	(-0.45)	(3.50)**	(0.21)	(3.52)**	(0.39)	(3.85)**	(2.14)**
MC		3.221		2.702		2.688		2.355
		(13.40)**		(12.89)**		(12.43)**		(9.93)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Over-Identifying Restriction Tests Test Statistics (p-value)	1.20 (0.55)	0.56 (0.75)	1.20 (0.55)	0.35 (0.84)	1.28 (0.53)	0.44 (0.80)	1.20 (0.55)	0.16 (0.92)
R^2	0.619	0.325	0.619	0.314	0.615	0.306	0.603	0.278
Observations	11,450	11,450	11,450	11,450	11,450	11,450	11,450	11,450

Panel B: The Determinants of RATING and UABOs								
	Model 1		Model 2		Model 3		Model 4	
	COST	APCT_ TB30Y	COST	APCT_ _AAA20Y	COST	APCT_ _AAA25Y	COST	APCT_ _AAATM
UPBOs (instrumented)	-0.140		-0.166		-0.167		-0.190	
	(-5.57)**		(-5.49)**		(-5.47)**		(-5.30)**	
COST (instrumented)		-0.060		-0.023		-0.043		-0.043
		(-0.89)		(-0.40)		(-0.72)		(-0.67)
BETA	0.121		0.120		0.120		0.115	
	(2.01)**		(1.98)**		(1.99)**		(1.87)*	
ASTD	0.260	-0.095	0.262	-0.083	0.260	-0.093	0.263	-0.079
	(2.69)**	(-0.58)	(2.71)**	(-0.58)	(2.67)**	(-0.62)	(2.67)**	(-0.49)
ME	0.044	-0.084	0.045	-0.059	0.044	-0.069	0.040	-0.086
	(1.51)	(-1.82)*	(1.57)	(-1.44)	(1.51)	(-1.66)*	(1.37)	(-1.93)*
BM	2.996	-0.547	3.001	-0.453	2.996	-0.479	2.986	-0.463
	(21.28)**	(-1.47)	(21.31)**	(-1.39)	(21.16)**	(-1.43)	(20.67)**	(-1.28)
LLEV ***BB***	0.564	-0.707	0.567	-0.603	0.567	-0.587	0.558	-0.558
	(4.32)**	(-2.82)**	(4.34)**	(-2.77)**	(4.33)**	(-2.65)**	(4.15)**	(-2.28)**
LIQ	3.112		3.107		3.084		3.126	
	(4.81)*		(4.76)**		(4.73)*		(4.68)*	
INTCOV		-0.002		-0.002		-0.002		-0.002
		(-1.42)		(-1.10)		(-1.28)		(-1.12)
MARGIN	-1.433	1.761	-1.437	1.514	-1.438	1.477	-1.391	1.561
	(-3.66)**	(3.66)**	(-3.66)**	(3.57)**	(-3.67)**	(3.41)**	(-3.48)**	(3.28)**
LOSS		0.021		0.073		0.095		0.105
		(0.08)		(0.33)		(0.42)		(0.42)
TRANS	-3.833	-0.399	-3.815	-0.072	-3.801	-0.065	-3.819	-0.110
	(-3.28)**	(-0.23)	(-3.26)**	(-0.05)	(-3.24)**	(-0.04)	(-3.22)**	(-0.06)
OBS	0.178	-0.315	0.182	-0.242	0.178	-0.268	0.170	-0.275
	(5.25)**	(-4.82)**	(5.38)**	(-4.29)**	(5.23)**	(-4.60)**	(4.90)**	(-4.35)**
LGROW	10.593	-0.021	10.579	-0.404	10.581	-0.172	10.534	-0.361
	(24.61)**	(-0.02)	(24.55)**	(-0.48)	(24.45)**	(-0.19)	(24.17)**	(-0.38)
IND_COST	0.475		0.477		0.475		0.475	
	(20.58)**		(20.50)**		(20.49)**		(20.30)**	
TB1Y	0.124	0.618	0.122	0.508	0.129	0.549	0.140	0.539
	(3.47)**	(9.42)**	(3.41)**	(8.97)**	(3.55)**	(9.27)**	(3.69)**	(8.89)**
FS	0.019	-0.009	0.021	0.005	0.022	0.008	0.028	0.043
	(3.33)**	(-0.41)	(3.52)**	(0.25)	(3.54)**	(0.44)	(3.86)**	(2.13)**
MC		2.886		2.442		2.427		2.130
		(13.42)**		(12.91)**		(12.45)**		(10.07)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Over-Identifying Restriction Tests Test Statistics (p-value)	1.19 (0.55)	0.14 (0.93)	1.34 (0.51)	0.07 (0.97)	1.24 (0.54)	0.11 (0.95)	1.16 (0.56)	0.03 (0.99)
R^2	0.620	0.337	0.617	0.324	0.616	0.316	0.606	0.288
Observations	11,450	11,450	11,450	11,450	11,450	11,450	11,450	11,450

Note: The sample covers 11,450 firm-year observations from 1,217 firms from October 1988 to June 2013. This table reports the two-stage least square (2SLS) regressions for the determinants of individual firms' cost of equity and understated pension liabilities. In Panel A, the two structural equations are (1) *COST* = linear function(*USPL*, *Z*) and (2) *UPBO*=linear function(*COST*, *Z*), where *COST* is the simple average of four individual measures of cost of equity (*COST_GLS*, *COST_CT*, *COST_OJ*, and *COST_PE*). *UPBO* refers to understated PBOs (*PCT_TB30Y*, *PCT_AAA20Y*, *PCT_AAA25Y*, and *PCT_AAATM*). *Z* is the set of exogenous variables, including the constant intercept, *ME_INF*, *COVERAGE*, *MARGIN*, *LLEV*, *PPE*, *BETA*, *R2*, *TRANS*, *TB1Y*, *FS*, *MC*, year dummies, and industry dummies. In Panel B, the two structural equations are (1) *COST* = linear function(*UABO*, *Z*) and (2) *UABO* = linear function(*COST*, *Z*), where *UABO* refers to understated ABOs (*APCT_TB30Y*, *APCT_AAA20Y*, *APCT_AAA25Y*, and *APCT_AAATM*). *TB1Y* denotes the yield on one-year Treasury notes. The table also reports the over-identifying restriction tests for the model specifications. ** indicates significance at the 5% level; * indicates significance at the 10% level. Petersen [2009] one-dimension firm-clustered t-statistics are reported.

11. Conclusions

Defined benefit corporate pension plans were once popular ways to arrange retirement benefits for U.S. employees. That has changed over time as more firms switch to defined contribution plans—passing the risk of having sufficient funds to finance retirement to their employees. Indeed, the advisory firm Willis Towers Watson, estimates that only about 14% of Fortune 500 firms offered a defined benefit plan in some form to their employees in 2019 versus 59% in 1998.[9] Nevertheless, the amount of assets in private defined benefit plans of all types in the USA remains huge with almost $3 trillion in assets across all defined benefit plans as of 2018 according to a 2021 U.S. Department of Labor report. The valuation of the corresponding huge defined benefit pension obligations critically depends on pension discount rates, among other pension parameters, because of the long-term nature of pension obligations. Firms have considerable discretion in choosing their pension discount rate. We examine the value of PBOs and ABOs if firms strictly follow the guideline interest rate benchmarks and compare them with reported PBOs and ABOs. We find that most firms in our sample choose pension discount rates that are higher than the 30-year Treasury bond and 20-year and 25-year AAA-grade corporate bond yields. This leads to understated pension PBOs and ABOs. We further show that these hidden pension liabilities significantly increase firms' implied cost of equity, suggesting that the market is not misled by intentional or unintentional discretion in choosing pension discount rates. Our results are robust after taking into account traditional control variables and important pension information such as funded status and mandatory contributions.

Unlike standard control variables, pension information appears in the notes of 10-K reports. Therefore, the disclosure level is much lower than earnings-based information risk proxies that directly appear in financial statements. Hirst and Hopkins [1998]and Davis-Friday and Folami [1999] show that the way accounting information is presented, organized, and processed affects valuation by investors and analysts. Plumlee [2003] concludes that complexity reduces analysts' use of information. Users of financial reports need to sort through voluminous notes to effectively forecast future earnings and adjust their valuation of firms. In addition, pension related numbers and their implications can be difficult for even sophisticated investors to gauge and reconcile with financial statements. Despite all these difficulties, our results show that stock market investors detect these hidden liabilities and adjust their valuation and earnings forecasts accordingly.

References

Andonov, A., R. Bauer, and M. Cremers, 2013, Pension fund asset allocation and liability discount rates: Camouflage and reckless risk taking by U.S. public plans?, Working Paper, University of Notre Dame, IN 46556.

Bergstresser, D., M. Desai, and J. Rauh, 2006, Earnings manipulation, pension assumptions, and managerial investment decisions, Quarterly Journal of Economics 121, 157–195.

Bhattacharya, U., H. Daouk, and M. Welker, 2003, The world price of earnings opacity, Accounting Review 78, 641–678.

Black, F., 1989, Should you use stocks to hedge your pension liability?, Financial Analyst Journal, January/February, 10-12.

Botosan, C., and M. Plumlee, 2005, Assessing alternative proxies for the expected risk premium, Accounting Review 80, 21–53.

[9] McFarland, Brendan, "Retirement Offerings in the Fortune 500: 1998-2019," Willis Towers Watson, https://www.willistowerswatson.com/en-US/Insights/2020/06/retirement-offerings-in-the-fortune-500-1998-2019

Botosan, C., M. Plumlee, and Y. Xie, 2004, The role of information precision in determining the cost of equity capital, Review of Accounting Studies 9, 233–259.

Brown, J., and D. Wilcox, 2009, Discounting state and local pension liabilities, American Economic Review 99, 538–542.

Campbell, J., D. Dhaliwal, and W. Schwartz, Jr., 2012, Financing constraints and the cost of capital: Evidence from the funding of corporate pension plans, Review of Financial Studies 25, 868–912.

Claus, J., and J. Thomas, 2001, Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets, Journal of Finance 56, 1629–1666.

Core, J., W. Guay, and R. Verdi, 2008, Is accruals quality priced as a factor?, Journal of Accounting and Economics 46, 2–22.

Coronado, J., and S. Sharpe, 2003, Did pension plan accounting contribute to a stock market bubble?, Brookings Papers on Economic Activity, 323–371.

Davis-Friday, P., and L. Folami, 1999, The value relevance of financial statement recognition vs. disclosure: Evidence from SFAS No. 106, Accounting Review 74, 403–423.

Diamond, D., and R. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, Journal of Finance 46, 1325–1359.

Easley, D., and M. O'Hara, 2004, Information and the cost of capital, Journal of Finance 59, 1553–1583.

Easton, P., 2004, PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital, Accounting Review 79, 73–95.

Ecker, F., J. Francis, I. Kim, P. Olsson, and K. Schipper, 2006, A returns-based representation of earnings quality, Accounting Review 81, 749–780.

Elton, E, 1999, Expected return, realized return and asset pricing tests, Journal of Finance 54, 1199–1220.

Fama, E., and K. French, 1997, Industry costs of equity, Journal of Financial Economics 43, 153–194.

Feldstein, M., and R. Morck, 1983, Pension funding decisions, interest rate assumptions, and share prices, In: Bodie, Z., and J. Shoven (Eds.), Financial Aspects of the United States Pension System, National Bureau of Economic Research Project Report Series, University of Chicago Press, Chicago, Illinois, pp. 177–210.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2004, Costs of equity and earnings attributes, Accounting Review 79, 967–1010.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The market pricing of accruals quality, Journal of Accounting and Economics 39, 295–327.

Franzoni, F., and J. Marín, 2006, Pension plan funding and stock market efficiency, Journal of Finance 61, 921–952.

Gebhardt, W., C. Lee, and B., Swaminathan, 2001, Toward an implied cost of capital, Journal of Accounting Research 39, 135–176.

Gode, D., and P. Mohanram, 2003, Inferring the cost of capital using the Ohlson-Juettner model, Review of Accounting Studies 8, 399–431.

Gordon, J., 1962, The investment, financing and valuation of the corporation, Irwin, Homewood, IL.

Hann, R., Y. Lu, and K. Subramanyam, 2007, Uniformity versus flexibility: Evidence from pricing of the pension obligation, Accounting Review 82, 107–137.

Hirst, D., and P. Hopkins, 1998, Comprehensive income reporting and analysts' valuation judgments, Journal of Accounting Research 36, 47–75.

Lambert, R., C. Leuz, and R. Verrecchia , 2007, Accounting information, disclosure, and the cost of capital, Journal of Accounting Research 45, 385–420.

Leuz, C., and P. Wysocki, 2008, Economic consequences of financial reporting and disclosure regulation: A review and suggestions for future research, Working Paper, University of Chicago, Chicago, IL 60637.

Liu, M., and P. Wysocki, 2008, Cross-sectional determinants of information quality proxies and cost of capital, AAA 2008 Financial Accounting and Reporting Section (FARS) Paper, Pennsylvania State University, PA 16802.

Lucas, D., and S. Zeldes, 2006, Valuing and hedging defined benefit pension obligations: The role of stocks revisited, Working Paper, Massachusetts Institute of Technology, Cambridge, MA 02142.

Lucas, D., and S. Zeldes, 2009, How should public pension plans invest?, American Economic Review 99, 527–532.

Mathur, R., G. Jonas, and M. LaMonte, 2006, Pension reform will increase funding requirements for under-funded U.S. pension plans, Moody's Special Comment.

McFarland, Brendan, "Retirement Offerings in the Fortune 500: 1998-2019," Willis Towers Watson, https://www.willistowerswatson.com/en-US/Insights/2020/06/retirement-offerings-in-the-fortune-500-1998-2019

McInnis, J., 2010, Earnings smoothness, average returns, and implied cost of equity capital, Accounting Review 85, 315–341.

Nichols, D., 2006, Fundamental risk or information risk? An analysis of the residual accrual volatility factor, Working Paper, Cornell University, NY 14853.

Novy-Marx, R., and J. Rauh, 2009, The liabilities and risks of state-sponsored pension plans, Journal of Economic Perspectives 23, 191–210.

Novy-Marx, R., and J. Rauh, 2011, Public pension promises: How big are they and what are they worth?, Journal of Finance 66, 1211–1249.

Ogneva, M., 2012, Accrual quality, realized returns, and expected returns: The importance of controlling for cash flow shocks, Accounting Review 87, 1415–1444.

O'Hara, M., 2003, Presidential address: Liquidity and price discovery, Journal of Finance 58, 1335–1354.

Ohlson, J., 1980, Financial ratios and the probabilistic prediction of bankruptcy, Journal of Accounting Research 18, 109-131.

Ohlson, J., and B. Juettner-Nauroth, 2005, Expected EPS and EPS growth as determinants of value, Review of Accounting Studies 10, 349–365.

Petersen, M., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, Review of Financial Studies 22, 435-480.

Picconi, M., 2006, The perils of pensions: Does pension accounting lead investors and analysts astray?, Accounting Review 81, 925–955.

Plumlee, M. 2003, The effect of information complexity on analysts' use of that information, Accounting Review 78, 275–296.

Rauh, J., 2006, Investment and financing constraints: Evidence from the funding of corporate pension plans, Journal of Finance 61, 33–71.

Stock, J., J. Wright, and M. Yogo, 2002, A Survey of weak instruments and weak identification in generalized method of moments, Journal of Business & Economic Statistics 20, 518–529.

Stock, J., and M. Yogo, 2002, Testing for weak instruments in linear IV regression, Working Paper 284, National Bureau of Economic Research.

Verdi, R., 2006, Information environment and the cost of equity capital, Working Paper, Massachusetts Institute of Technology, MA 02142.

U.S. Department of Labor, 2021, Private pension plan bulletin historical tables and graphs 1975-2018, Employee Benefits Security Administration, U.S. Department of Labor, January 2021, Table E-10, page 13.

https://www.dol.gov/sites/dolgov/files/ebsa/researchers/statistics/retirement-bulletins/private-pension-plan-bulletin-historical-tables-and-graphs.pdf