

Toan Luu Duc HUYNH

Essays on Market Reaction and Cryptocurrency

Dissertation

for obtaining the degree of Doctor of Business and Economics
(Doctor rerum politicarum - Dr. rer. pol.)
at **WHU – Otto Beisheim School of Management**

January 25, 2022

First Advisor: Prof. Dr. Mei Wang
Second Advisor: Prof. Dr. Ralf Fendel

“It does not matter how slowly you go as long as you do not stop.”

- Confucius

WHU – OTTO BEISHEIM SCHOOL OF MANAGEMENT

Abstract

Chair of Behavioral Finance

Doctor of Philosophy

Essays on Market Reaction and Cryptocurrency

by Toan Luu Duc HUYNH

In the decade following the 2008 financial crisis, the coronavirus viral disease 2019 (COVID-19) pandemic and United States (US) President Trump's Twitter account became representations of market uncertainty, attracting the financial research of (Goodell, 2020; Benton and Philips, 2020). Due to the popularity of these events and their impact on financial markets, many unanswered questions still persist, particularly, how the financial structure has changed during this unique time. The popularity of Bitcoin, one of the main cryptocurrencies, has caused a controversial topic to arise in recent academic research, namely, whether its function compares to that of conventional precious metals such as gold and platinum. This doctoral thesis aims to fill this research gap in two ways: (i) by addressing market reactions to the COVID-19 pandemic and political news by answering the question of how US legislators traded at an industry level during the ongoing COVID-19 pandemic, and how Trump's Twitter account could shake the equity market during a trade war, and (ii) by examining the power of the gold and platinum ratio, which was first studied by (Huang and Kilic, 2019), in predicting Bitcoin as well as how political sentiment could drive the returns, volatility, and volume of this cryptocurrency. This thesis contributes to the empirical evidence in the areas mentioned above due to the growing attention on the financial function of cryptocurrency, the debatable effects of political news regarding the use of social media, and the eventual and unprecedented scale of the COVID-19 pandemic.

Acknowledgments

The Ph.D. journey offered me a chance to enjoy the academic life with many pieces of joy, but it was not easy. This thesis would not have been possible without the endless support and help of many great people who deserve my highest gratitude.

First and foremost, I would like to thank my first supervisor, Mei Wang, for acting as an academic advisor and mentor in life. Not only did she provide me the excellent opportunity to conduct some fascinating studies at the Chair of Behavioral Finance, cultivating an interest in science, but she also encourages me to espouse liberalism and highly influences me to become an economist as well as a social scientist. I am greatly grateful for our fruitful and insightful discussion over the years, helping me consider carefully my future research. Our meetings in her office, restaurants, train (from Koblenz to Trier), and even on the way to the bus station to discuss my research and talk about my motherhood, family life, and my future career have made my doctoral journey enjoyable. Her tolerant, sincere, and supportive manner has been intellectually stimulating and inspiring to interact with her on academic and personal topics. I also thank her for encouraging me to be confident and bold, although I am typically timid. Finally, I owe her a debt of gratitude for patiently guiding me through the academic process and unconditionally providing care as a member of her family. Also, sincere thanks to Marc Oliver Rieger for introducing me to Mei and sharing a voluminous experience to my doctoral journey.

I sincerely thank my second advisor, Ralf Fendel, for his extensive advice and guidance. Especially, I would like to express my appreciation to thank him for encouraging me to ask ‘big questions’ in both the research field and even on my job market. Moreover, our occasional online meetings (between Germany and Vietnam) and lively discussions on all sorts of topics have considerably influenced the formation of my academic thoughts. I have been lucky to benefit from his experienced advice and insights into academic life, which has been extremely valuable and inspiring in setting my research agenda. His dedication to students is the most valuable attribute I hope to take with me in my future endeavors in academia.

I am also grateful to Daniel Schunk, Steffen Altmann, Alexander Sebald, Roberto Fumagalli, Christina Gravert, and Peter-J. Jost for their enthusiastic and insightful lectures during my doctoral courses. In addition, the Finance and Accounting Group of the WHU - Otto Beisheim School of Management has been a place filled with full of nice and supportive colleagues. I thank Anja Ziegler for her excellent help and support in a variety of requests over the last three years. Thank you, Anja, for being an inseparable companion and sharing with me through the many ups and downs of my doctoral life. I could have probably not understood and felt the German culture without you and your hospitality. You have enriched my world outside of research. Several colleagues and friends at the WHU community have helped to make the years

in Vallendar such special ones. I especially thank Michael Frenkel, Rainer Michael Rilke, Jiachun Lu for many inspirational discussions. I feel fortunate to have spent endless hours chatting next to my fellow doctoral students and friends, Mustafa Kilinc, Armin Klomfass, Quynh Pham, Maximilian Ambros, Haiko Stefan, Tuyet Ngo, Diep Tran, Nabil Alkafri, Sina Timm, Reza Fathollahi, and Sebastian Seidens. The 1st floor (D-building) is an awesome office home thanks to Niklas Meyer, Basma Heidar, Robert Vossebürger, and Thorben Wulff with occasional lunches and the times of fun together. Special thanks to Can Deniz Dogan for being my emotional anchor. I also thank Gongjue Tian and Qinghang Wu for playing the role of a sister in the doctoral program by chatting, sharing, and learning together. Last but not least, I would like to thank all doctoral office colleagues, particularly Claudia Heymann, Diana Britscho, as well as the IT Department for helping me during my the doctoral study. They really make this such a smooth process.

I am so lucky to have formed coauthorship with John W. Goodell and Tobias Burggraf. I especially thank John W. Goodell, who helped me significantly to grow as a researcher from your valuable experience. Likewise, I would like to thank my dear friend, Tobias Burggraf, for your excellent work, generous provision of comments, and always being readily available for working on our manuscripts even late evening or early morning. With you, my journey has been an incredible amount of joy. Then, we have grown together throughout every step of this challenging journey. I always look forward to many more years of friendship and coauthors.

Likewise, I would like to thank my friends Duy Tra, Minh-Hau Bui, Huong Tram, Thi-Nhan Nguyen, Hien-Thu Nguyen, Hai-Minh Ngo, Tam-Thanh Tran, Thuy-Chung Phan, Huy (Eric) Phan, Ha Nguyen, Ngan Nguyen, Muhammad Ali Nasir, Thong Trung, Bao-Anh Phan, Duy Duong, Thach-Ngoc Ly, Huyen Nguyen, Nam Bui, Tuan Phan, Tan-Thong Nguyen, Kim-Ngoc Phan, Nhat-Quang Trinh, and Duyen-Ngoc Lai for making me feel closer to home when I was in Germany. We are bearing with each other through laughter and through tears after many friendship years. I also thank Hoai-Trong Nguyen, Minh-Huyen Dao, Peng-Fei Dai, Huy-Viet Hoang, Phuoc-Huu Le, and Anh Huynh for their generous support to complete this thesis.

Words cannot describe how grateful I am to my mom for her endless love and encouragement. She has always provided the necessary support and encouraged me to pursue whatever made me happy. She sacrificed everything for me and I am blessed to have her. This work is dedicated to her. To my grandparents for instilling in me to become a valuable person - I wish you could be here to read this work with me.

Contents

Abstract	ii
Acknowledgments	iii
1 Introduction	1
2 Political news and stock prices	5
2.1 Introduction	5
2.2 Data and Methodology	6
2.3 Results	6
2.4 Conclusion	9
3 Did Congress trade ahead?	10
3.1 Introduction	10
3.2 Data and methodology	12
3.2.1 Data	12
3.2.2 Methodology	12
Google searches and industry returns	12
Event study	14
3.3 Results	15
3.3.1 When did investor interest in COVID begin?	15
3.3.2 Impact of COVID-related investor attention	16
3.3.3 Abnormal returns	16
3.4 Conclusion	18
4 Gold, platinum, and expected Bitcoin returns	21
4.1 Introduction	21
4.1.1 Background	21
4.1.2 Motivation	22
4.2 Literature Review	23
4.3 Methodology	26
4.3.1 Wavelet multiple correlation	26
4.3.2 Quantile regression	27
4.3.3 General model specification	27
4.3.4 Forecast Error Variance Decompositions from VAR	28
4.4 Results	29
4.4.1 Data description	29

4.4.2	Wavelet Multiple Correlation Results	31
4.4.3	Bitcoin return predictability	33
4.4.4	Robustness check	37
4.5	Conclusion	40
5	Does Bitcoin react to Trump’s Tweets?	41
5.1	Introduction	41
5.2	Theoretical framework	43
5.3	Methodology	44
5.3.1	Textual analysis	44
5.3.2	Spillover effects	44
5.4	Data	45
5.5	Main findings	49
5.5.1	Regression and Causal relationship	49
5.5.2	Spillover effects of Trump’s sentiment on Bitcoin market	53
5.5.3	Trump attitudes towards COVID-19 pandemic and Bitcoin	55
5.5.4	Do Trump’s Tweets trigger the Bitcoin jumps?	57
5.5.5	Robustness check	57
5.6	Conclusion	59
6	Conclusion	60
A	Political news and stock prices: Evidence from Trump’s trade war	64
B	Did Congress trade ahead? Considering the reaction of US industries to COVID-19	68
C	Gold, Platinum, and expected Bitcoin returns	70
D	Does Bitcoin react to Trump’s Tweets?	72
E	Textual analysis code	78
	Bibliography	83

List of Figures

2.1	Average S&P 500 return with and without ‘Trump tweet’ by industries.	8
3.1	The time varying of Corona and COVID-19 searching terms in the US.	15
4.1	LogGP ratio and Log Bitcoin price	30
4.2	Wavelet multiple correlation for GP Ratio and Excessive Bitcoin Return	32
4.3	LogGP ratio and Excess Bitcoin Return	34
4.4	Spillovers from volatility by using 12-month window rolling	37
5.1	Time-varying between negative and positive from textual analysis.	46
5.2	Time-varying between Bitcoin prices and negative sentiment.	47
5.3	Average return and trading volume under two regimes	48
5.4	Time-varying spillover effects using a different-days rolling window	54
5.5	Net spillover effects by each component	55
B.1	Correlation matrix (Full sample).	68
B.2	Correlation matrix (After January 21, 2021).	69
B.3	Correlation matrix (Before January 21, 2021).	69
C.1	LogGP ratio and Excess Ethereum Return	71
D.1	Bitcoin volatility was estimated by the GARCH-in-mean (M-GARCH)	72
D.2	Bitcoin volatility was estimated by the Threshold-GARCH (T-GARCH)	77

List of Tables

2.1	Descriptive statistics of political news and stock prices	7
2.2	The impact of Trump tweets on S&P 500 and VIX	7
3.1	Descriptive statistics of 49 industries, market, and Corona attention . .	13
3.2	Summary of event, estimation window and excluded days	14
3.3	The impact of public focus on ‘corona’ on industry returns	17
3.4	The ARs and CARs across industries on February 26, 2020	19
4.1	Descriptive statistics of Gold-Platinum and excessive Bitcoin return . .	31
4.2	Stationary test	31
4.3	Bitcoin return predictability by Ordinary Least Squares	33
4.4	Bitcoin return predictability by Vector Auto Regressive (VAR)	35
4.5	Volatility spillover table rows (to), columns (from)	35
4.6	Bitcoin return predictability by quantile regression	38
4.7	Bitcoin return predictability with January effect sub-sample	38
4.8	Descriptive statistics for daily data	39
4.9	Bitcoin predictability by Ordinary Least Squares with data from Bitstamp	39
5.1	Descriptive statistics of Bitcoin and Trump’s sentiment	46
5.2	Impact of Trump’s sentiment on contemporaneous Bitcoin returns	49
5.3	Impact of Trump’s sentiment on daily contemporaneous Bitcoin volume	50
5.4	Impact of Trump’s sentiment on monthly contemporaneous BTC volatility	51
5.5	Vector Autoregressive Granger causality	52
5.6	Trump sentiment and long-term spillovers on volatility	53
5.7	Impact of Trump’s sentiment regarding COVID-19 on Bitcoin market . .	56
5.8	The predictive power of Trump’s Tweets on the Bitcoin’s jumps	58
A.1	Robustness Test: Vector autoregressions with Placebo Tweet	64
A.2	Robustness Test: Granger causality tests with Placebo Tweet	65
A.3	Robustness Test: Vector autoregressions with the Dow Jones	65
A.4	Robustness Test: Granger causality tests with the Dow Jones	65
A.5	Industry test: Summary of VAR tests for industry	66
A.6	Industry test: Summary of SVAR tests for industry	66
A.7	Industry test: Differences in return across industries	67
C.1	Descriptive statistics for Ethereum and logGP	70
C.2	Ethereum predictability by OLS with data from Bitstamp	70

D.1	Impact of Trump's sentiment on Bitcoin volatility, captured by M-GARCH	73
D.2	Impact of Trump's sentiment on Bitcoin volatility, captured by T-GARCH	74
D.3	Impact of Trump's sentiment on contemporaneous ETH returns	75
D.4	The predictive power of Trump sentiment on the ratio Gold-Platinum	76

List of Abbreviations

ADF	A ugmented D ickey– F uller
AIC	A kaike I nformation C riterion
AMEX	A merican S tock E Xchange
API	A pplication P rogramming I nterface
AR	A bnormal R eturn
ARDL	A uto R egressive D istributed L ag
BRICS	B razil, R ussia, I ndia, C hina, and S outh A frica
BTC	B i T Coin
CAPM	C apital A sset P ricing M odel
CAR	C umulative A bnormal R eturn
CBOE	C hicago B oard O ptions E xchange
CDC	C enters for D isease C ontrol and P revention
CDS	C redit D efault S wap
COVID	C ORona V irus D isease
CRSP	C enter for R esearch in S ecurity P rices
DAX	D eutscher A ktieninde X
EBR	E xcessive B itcoin R eturn
EPU	E conomic P olicy U ncertainty
ETH	E T H ereum
EURO	E U R Opean M onetary U nit
FEARS	F inancial and E conomic A ttitudes R evealed by S earch
FOMC	F ederal O pen M arket C ommittee
GARCH	G eneralized A utoregressive C onditional H eteroscedasticity
GDP	G ross D omestic P roduct
GP	G old P latinum
GPU	G raphics P rocessing U nits
HAC	H eteroskedasticity, A utocorrelation C onsistent
JB	J arque- B era
JP Morgan	J ohn P ierpont M organ
KAABA	K orean A cademic A ssociation of B usiness A dministration
MERS	M iddle E ast R espiratory S yndrome coronavirus
MODWT	M aximal O verlap D iscrete W avelet T ransform
MSCI	M organ S tanley C apital I nternational
NASDAQ	N ational A ssociation of S ecurities D ealers A utomated Q otation
NYSE	N ew Y ork S tock E xchange
OLS	O rdinary L east S quare

PHEIC	P ublic H ealth E mergency of I nternational C oncern
PP	P hillips– P erron
SARS	S evere A cute R espiratory S yndrome
SD	S tandard D eviation
SIC	S chwarz I nformation C riterion
SVAR	S tructural V ector A uto R egression
UK	U nited K ingdom
US	U nited S tates
VAR	V ector A uto R egression
VECM	V ector E rror C orrection M odel
VIF	V ariance I nflation F actor
VIX	V olatility I nde X
WHO	W orld H ealth O rganization
WMCC	W avelet M ultiple C ross C orrelation
WTI	W est T exas I ntermediate

Chapter 1

Introduction

Since the financial crisis ended in 2009, the world has witnessed two unexpected events that have had a substantial influence on financial markets. The first is the victory of Donald J. Trump as the 45th president of the United States (US) on November 8, 2016. The second is the outbreak of the novel coronavirus disease 2019 (COVID-19), which was declared as Public Health Risk Emergency of International Concern on January 30, 2020 by the World Health Organization (WHO).

Ranco and Mozetič (2015) claimed that institutional investors have kept track of a vast amount of political, social, and economic information, which intentionally or unintentionally induces investor sentiment. Interestingly, Donald Trump's Twitter account is controversial because this is the first US president to use social media to express his ideas with the utmost indifference to his predecessors. In this context, JP Morgan Chase also created a novel index called the 'Volfefe Index' to quantify how President Trump's Twitter account influences financial markets. Recently, Klaus and Koser (2020) employed a rolling-window regression model to examine the relationship between Trump's tweets and the European stock market's performance after controlling for the relevant factors. In the same vein, Wagner, Zeckhauser, and Ziegler (2018) concluded that Trump's election shifted investors' expectations due to the unexpected changes in taxation, trade, and tariff policies. One of the most influential policies is the Trump administration's US-China trade war, which had been looming since January 2018. While the situation has calmed down, it was previously an unprecedented event in contemporary history. This conflict context poses the following question: could Trump's sentiment towards the trade war destabilize financial markets? Because this event represents not only national conflict but also a disruption of the global supply chain (Mao and Görg, 2020). Examining this question is the first motivation of this thesis.

The ongoing COVID-19 pandemic has garnered significant attention from not only media outlets but also public broadcasters such as Haroon and Rizvi (2020). Although an argument exists that COVID-19 poses a fearsome and novel risk, this pandemic could be considered an ideal environment for exploiting asymmetrical information by trading ahead of financial markets and generating positive returns. At present, there are many studies that have examined how the COVID-19 pandemic influenced financial markets from a variety of perspectives (Zhang, Hu, and Ji, 2020; Goodell, 2020; Baker

et al., 2020; Schell, Wang, and Huynh, 2020). However, there is still a research gap in terms of investigating the stock market's reaction to COVID-19 news announcements by several US legislators as well as Google searches and financial markets. This is the second motivation for this thesis.

The market value of cryptocurrency now exceeds the gross domestic product (GDP) of 130 countries (Selmi, Tiwari, Hammoudeh, et al., 2018). While investors and researchers ask, 'What drives Bitcoin returns?', contemporaneous studies answer by referencing supply and demand (Ciaian, Rajcaniova, and Kancs, 2016), macroeconomic news (or the US Federal Funds interest rate and quantitative easing announcements) (Corbet et al., 2020b; Corbet et al., 2020a), and economic policy uncertainty (Demir et al., 2018). The current literature confirms the effects of social media and public broadcasters on Bitcoin returns (Urquhart, 2016; Urquhart, 2018; Shen, Urquhart, and Wang, 2019). Beyond that, Trump's Twitter account conveys political information and policies that might drive Bitcoin's returns, volatility, and trading volume. While Bitcoin has been controversially known as 'Digital Gold'¹, the characteristics of Bitcoin as digital gold is still an ongoing debate. Some previous studies have claimed that Bitcoin exhibits superior resilience during periods of financial distress (Popper, 2015; Bouri et al., 2017). While there is mounting evidence confirming the predictive power of the gold–platinum (GP) ratio to equity markets (Huang and Kilic, 2019), bond risk premia (Bouri et al., 2020), the Chinese stock market (Han, Ruan, and Tan, 2020), and so on, the predictive power of this ratio is not applied in the pricing of cryptocurrency assets. The economic rationale for using this ratio to predict Bitcoin returns is the opportunity cost of alternative investments with an increase in aggregate market risk, representing variations in the natural logarithm of the GP ratio. For the aforementioned reasons, investigating the predictive power of this ratio and Trump's Twitter account is the third main motivation for examining cryptocurrency investments.

While the world experiences unexpected losses from the newly emerging pandemic and the resultant political uncertainty, the Bitcoin price reached a new peak of \$13,519.77² as expectations rose for its function as a safe haven during this tumultuous time. Cryptocurrencies might become an alternative investment to hedge against the potential risks of future uncertainty. This concern has not yet been addressed. Therefore, examining cryptocurrency investment is not only a fascinating topic, but also provides a greater understanding of financial stability. Concomitantly, during this age of Twitter popularity, the study of President Trump's Twitter account might explain the financial mechanisms underlying returns movements in classical investments (e.g., the US equity indices and industry-level analysis) and in digital currencies (e.g., Bitcoin). More importantly, the initial losses of financial markets caused by the COVID-19 pandemic

¹This point does not only result from academic research, but also from industry perspectives. The term 'digital gold' refers to Bitcoin's detachment from centralized government mechanisms, which enables people and investors to preserve wealth in a secure way.

²See <https://coinmarketcap.com/currencies/bitcoin/> at 3rd November 2020

are still being assessed as the second wave is currently underway. Obviously, the recent spread of the COVID-19 pandemic is a distinctive natural experiment for conducting financial research. This effect certainly offers an opportunity to assess the dynamics of financial markets, including stock and Bitcoin, in this thesis.

This thesis is structured as follows. There are two main parts—the market reactions and the cryptocurrency study. Chapter 2 provides empirical evidence that political news could impact financial markets from Trump’s trade war. Chapter 3 covers industry market reactions to three notable news releases and investors’ trading behavior at the onset of the COVID-19 pandemic. Chapter 2 and 3 are both classified as market reaction. The remaining part consists of another two projects. Chapter 4 investigates the predictive power of the GP ratio for Bitcoin returns. Finally, my thesis concludes with chapter 5, which explains how Trump’s Twitter account functions as a proxy for presidential sentiment and could therefore influence the Bitcoin market.

Chapter 2 provides an empirical evidence about the impact of political news on stock price movements. Analysing more than 3,200 tweets from US President Donald Trump’s Twitter account, the study finds that tweets related to the US-China trade war negatively predict S&P 500 returns and positively predict CBOE Volatility Index (VIX). Granger causality estimates indicate that the causal relationship is one-directional – from Trump tweets to returns and VIX. Finally, the results vary across industries depending on their degree of trade intensity with China (Burggraf, Fendel, and Huynh, 2019). Chapter 3 sets out to explore the market reactions on the onset of COVID-19 pandemic. During the ongoing COVID-19 pandemic in the US, there has been considerable media attention regarding several US legislators who traded stocks from late January through February 2020. The concern is that these legislators traded in anticipation of COVID-19 having a major impact on the financial markets, while publicly suggesting otherwise. This study considers whether these legislator trades were in a time window, and of a nature, that would be consistent with trading ahead of the market. Towards this end, the reactions of US industries to sudden COVID-related news announcements are examined, concomitantly with an analysis of levels of investor attention to COVID. Results suggest that, at an industry-level, for legislator trading to be “ahead of the market” it needed to have been done prior to February 26, and involved the 15 industries we identify as having abnormal returns, especially medical and pharmaceutical products (positive); restaurants, hotels, and motels (negative); as well as services and utilities. These criteria are met by many of the legislator trades. The results help to both parameterize concerns about this case of legislator trading; as well as provide insight into the reactions and expectations of investors toward COVID-19 (Goodell and Huynh, 2020). The next chapter (Chapter 4) examines the prediction power of the ratio of gold to platinum prices (GP) on Bitcoin. By using different models and data sources for Bitcoin, this chapter finds that GP predicts future Bitcoin return. When the price of gold relative to platinum increases, Bitcoin return also goes

up. This finding is consistent with previous studies and contributes to the ongoing discussion whether GP can be used as an indicator for aggregate market risk. Using variance decomposition, the study also explores that volatility in the gold and platinum market can influence Bitcoin volatility and that this relationship shows time-varying dependency. Finally, the results are robust to including new year effects and data of different frequencies. Hence, this paper contributes to the current literature of Bitcoin by showing that GP provides an important proxy of risk in the economy (Huynh, Burggraf, and Wang, 2020). Finally, chapter 5 having textual analysis with spillover effects examines whether the sentiment expressed in the US President Donald Trump's tweets correlates to price and volume activity in the Bitcoin market. After examining 13,918 tweets from January 2017 to January 2020, this chapter finds that negative sentiment is a predictive factor for Bitcoin returns, trading volumes, realized volatility, and jumps. In addition, only negative sentiment has a Granger-causal relation with volatility. This final chapter also finds that Trump's Twitter sentiment can influence the Bitcoin market in the form of time-varying dependence. This paper also extended the COVID-19 period and found that Trump's sentiment can be a predictive tool to the Bitcoin market during the pandemic. The results hold robust for alternative cryptocurrencies and offer insights into this market (Huynh, 2021).

Chapter 2

Political news and stock prices: Evidence from Trump's trade war[†]

2.1 Introduction

Donald Trump's use of social media is controversial. Having used Twitter more than 16,000 times¹ since his official declaration of candidacy in June 2015, his tweets are often brash, petulant and unpredictable. Yet, they capture the attention of a wide audience, for better or worse. By anecdotic evidence, on the 5th of May 2019, he announced via Twitter to place additional tariffs on \$200 billion of imported Chinese goods – Two tweets and 102 words that wiped off about \$1.36 trillion of global stocks². The renewed hostilities between the two economic giants raise the question of how many tweets from Donald Trump can swing stock markets.

Academic research on the effects of political news on stock returns has not been conclusive. Cutler, Poterba, and Summers (1989) find a 'surprisingly small effect' of elections and international conflicts, Riley and Luksetich (1980) and Herbst and Slinkman (1984) find significant negative price changes before presidential elections. Harms (2002) evaluates the importance of political risk on equity returns and, more recently, Raimundo Júnior et al. (2019) confirm the role of political risk by analyzing beta herding effects. In this study, we investigate whether political news leaked by tweets from Donald Trump negatively influence stock markets. While previous studies such as Zhang, Fuehres, and Gloor (2011) and Azar and Lo (2016) focus on aggregated public mood measured by Twitter sentiment, this is the first study to examine the impact of an individual's Twitter activities. There are two major factors that prompt us to link Trump's Twitter account to stock market returns. First, President Trump is among the most controversial users of the platform. He uses Twitter extensively and captures the attention of a wide audience. Second, every political move is documented in his Twitter account and is often 'leaked' on Twitter before the official announcement. Even the White House recently clarified that his tweets represent presidential statements, carrying the

[†]This chapter is based on Burggraf, T., Fendel, R., Huynh, T. L. D. (2020). Political news and stock prices: evidence from Trump's trade war. *Applied Economics Letters*, 27(18), 1485-1488, <https://doi.org/10.1080/13504851.2019.1690626>.

¹Trump tweeted 16,752 times from June 2015 to June 2019, according to the his Twitter Archive website.

²'Each Word of Trump's Tariff Tweets Wiped \$13 Billion Off Stocks' (Bloomberg article) on May 8, 2019.

same imprimatur as a comment issued by his press office³. The rest of this paper is structured as follows. Section 2.2 introduces the data and methodologies. Section 2.3 summarizes our empirical results. We conclude in section 2.4.

2.2 Data and Methodology

Tweets from Donald Trump’s Twitter account *@realDonaldTrump* including timestamps in minutes are scrapped from Twitter. Because the Twitter API only allows to return up to 3,200 of a user’s most recent tweets, we limit our sample to the period 14.09.2018 – 28.05.2019. In the next step, we filter the sample using the following keywords: ‘China’, ‘trade’, ‘trade war’ and ‘tariffs’. This leaves us with 224 tweets. Subsequently, retweets and tweets not related to the trade war between the US and China are eliminated. Tweets on the weekend are treated as Friday tweets, i.e. Saturday and Sunday tweets are $(t - 1)$ tweets for subsequent Monday returns. Our final sample includes 77 tweets. Daily closing indices for the S&P 500, VIX (our main test) are retrieved from Refinitiv. We use different equity indices⁴ and macroeconomic factors⁵ to control the regressions. To test the influence of ‘Trump Tweets’ on various industry returns, we use the Fama-French portfolio industry by assigning each stock listed on the US exchange with industry code in the same time period.

To examine the impact of Trump tweets on financial markets, we use a Vector Autoregressive (VAR) model which fits a multivariate time-series regression of each dependent variable on lags of itself and on lags of all the other independent variables. Furthermore, to investigate the effects of Trump tweets on contemporaneous ($t=0$) S&P 500 return and VIX, we employ a Structural Vector Autoregressive (SVAR) model. After fitting our VAR model, we also investigate whether one variable ‘Granger-causes’ another variable by applying Granger (1969) causality test.

2.3 Results

Table 2.1 reports descriptive statistics. Average S&P 500 return is -0.00005 and the change in VIX is -0.01. The Jarque-Bera test of normality is rejected for all variables. To get a first impression of the impact of Trump tweets, we split our data into two subsamples: ‘with tweet’ and ‘without tweet’. There is a significant difference between average return ‘with tweet’ (-0.46%) and ‘without tweet’ (0.06%) (t-test, ρ -value < 0.01). In addition, we find a significant difference between average VIX ‘with tweet’ (-1.12%) and ‘without tweet’ (2.44%) (t-test, ρ < 0.05).

³On June 6, 2017, White House press-secretary Sean Spicer declared that Mr. Trump’s tweets are ‘official statements’.

⁴We use MSCI China, Nikkei, DAX, FTSE100, and EURO STOXX 50.

⁵We use the 3-month Treasury Bill rate, Economic Policy Uncertainty index, Industrial Production Index, and WTI crude-oil.

TABLE 2.1: Descriptive statistics of political news and stock prices

Variable	Mean	SD	Skewness	Kurtosis	Jarque-Bera
S&P 500	-0.00005	0.01	-0.04	5.73	82.4***
VIX	-0.01	0.08	0.82	5.03	75.17***
Tweet	0.13	0.33	2.27	6.14	334.9***

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.2 reports estimates of our VAR model. Trump tweets predict returns at more than one lag. While lag one tweets negatively predict returns, lag two tweets positively predict returns, but with lower magnitude. Therefore, we find evidence that the market reacts to Trump tweets but mean reverses in subsequent periods. However, this correcting effect cannot fully offset the shock from period $(t - 1)$. Both coefficients are statistically significant. In addition, we find that lag one Trump tweets significantly predict an increase in investor fear measured by VIX. Lag $(t - 2)$ tweets reduce risk again, but with lower magnitude. Finally, both lag one returns and lag one VIX positively predict returns.

TABLE 2.2: The impact of Trump tweets on S&P 500 and VIX

Variable	S&P 500 _(t)	VIX _(t)
S&P 500 _(t-1)	0.376*** (-0.11)	-0.654 (-0.903)
S&P 500 _(t-2)	0.009 (-0.106)	0.241 (-0.872)
VIX _(t-1)	0.030** (-0.001)	0.201 (-0.105)
VIX _(t-2)	-0.01 (-0.013)	0.009 (-0.108)
Tweet _(t-1)	-0.006*** (-0.002)	0.039** (-0.016)
Tweet _(t-2)	0.004** (-0.002)	-0.032** (-0.016)

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Control variables are used. Robust standard errors in parentheses.

To investigate the causal relationship between our three main variables, we apply a Granger causality test. We construct two hypotheses. H_{01} : Trump tweets do not Granger cause S&P 500 return, and H_{02} : Trump tweets do not Granger cause VIX. The first hypothesis is rejected (F-statistics: 10.664, ρ -value < 0.01). Therefore, we conclude that stocks fall when Donald Trump tweets about the trade war. The second hypothesis is also rejected (F-statistics: 8.138, ρ -value < 0.05). Hence, we can conclude that tweets from Donald Trump cause investor uncertainty measured by the ‘fear index’ VIX. When employing SVAR estimation, we find that tweets also impact contemporaneous S&P 500 return – when Donald Trump tweets ($\beta = -0.308$, ρ -value < 0.01),

the S&P 500 falls on the same day ($t = 0$). His tweets also trigger an increase in contemporaneous volatility ($\beta = 0.393$, ρ -value < 0.01) measured by the VIX.

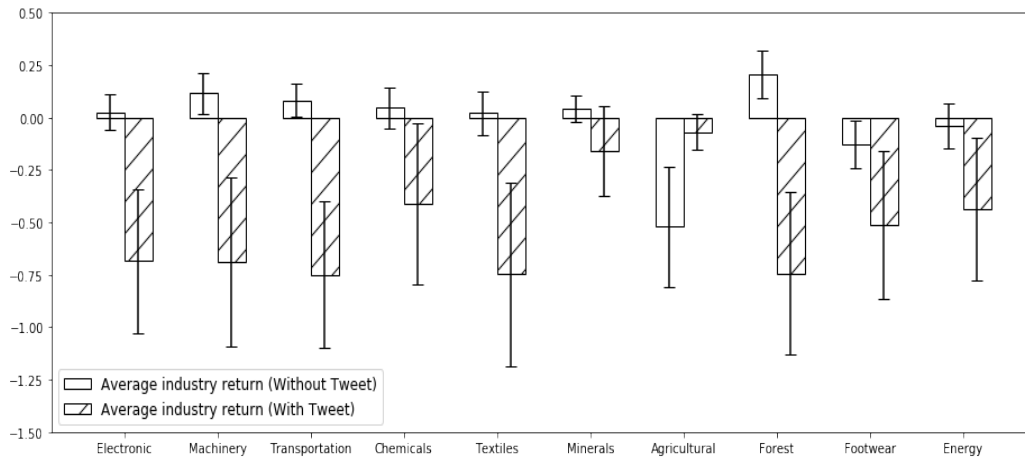


FIGURE 2.1: Average S&P 500 return with and without ‘Trump tweet’ by industries. Error bars are standard errors of the mean and industries are ranked by descending trade intensity.

One would assume that Trump’s tweets related to the US-China trade war should have a stronger impact on those firms that rely heavily on international trade, especially trade with China. In order to validate this point, we check with the U.S. International Trade Commission that the top three industries of US-China trading intensity (imports plus exports over total trade) in 2017 are electronic products (40.33%), machinery (11.47%) and transportation equipment (10.45%). As displayed in Figure 4.1, the reversed returns with ‘Trump tweet’ significantly appear in those sectors. Additionally, when running the same econometric analysis as before, but on an industry level, we find that ‘Trump tweets’ also predict negative contemporaneous industry return (by using SVAR) and one-lagged period return (by using VAR). Finally, we find that 9 out of 10 industries have a Granger causal relationship with ‘Trump tweet’⁶. The correlation between trade intensity and Trump tweets is 0.29. Therefore, both move in the same direction.

To assess the robustness of our results, we create a ‘placebo’ tweet variable including tweets from Donald Trump that mention China but which are not related to the US-China trade war. Performing the same VAR-Granger causality analysis, we do not find any evidence that placebo tweets significantly influence S&P 500 or VIX. We apply our model to the Dow Jones Industrial Average index. We find consistent results across both indices⁷.

⁶The results are available in Tables A.5 – A.7.

⁷The results are available in Tables A.1 – A.4

2.4 Conclusion

How many words do you need to shake up markets? We find evidence that one tweet or 280 characters are enough. Results from our VAR model indicate that tweets from Donald Trump have significant negative effects on stock prices and positive effects on VIX. The results vary over industries depending on their degree of trade openness with China. Granger causality estimates find one-directional causal relationships from Trump tweets to S&P 500 return and VIX. Finally, our results are robust using our placebo tweet variable and for the Dow Jones index as well.

Chapter 3

Did Congress trade ahead? Considering the reaction of US industries to COVID-19[‡]

3.1 Introduction

During the ongoing COVID-19 pandemic in the US, there has been considerable public and media attention regarding several US legislators who traded stocks from late January through February 2020. The concern is that these legislators traded in anticipation of COVID-19 having a major impact on the financial markets, while publicly suggesting otherwise. Roughly, the scenario is that two US senators, Richard Burr and Kelly Loeffler both sold large amounts of stock in late January through mid February. This was when US markets were at peak values. Both Burr and Loeffler received non-public information about the global spread of coronavirus from White House officials, who had been briefing Senators regularly for some weeks. The concern is not that either Burr or Loeffler received specific, material, non-public information and then used it to trade specific stock (qualifications for insider trading), but rather that their concomitant public assertions of market optimism violated the public trust. On Feb. 13, one week before U.S. stocks began sliding, Burr executed 33 trades, selling more than half a million dollars of shares (Aaron, 2020). Burr and Loeffler may have executed the largest magnitude of trading but they are by no means the only legislators under scrutiny. For instance, representative Susan Davis sold several thousand dollars of shares in Alaska Air and Royal Caribbean Cruise Lines on February 11 (Maggie and Katy, 2020). In some ways, the COVID-19 crisis presented an ideal environment for asymmetric information between government officials and the general public. Elected officials in the US were mindful of the political importance of economic and market optimism, while COVID-19 seemingly surprised many, particularly western, economies. Initially, many people evaluated the risk of COVID-19 as like a typical flu. Others, perhaps, may have regarded COVID-19 as an infectious disease, like SARS or MERS, would be mainly limited to some domestic outbreaks, especially in China (Fan et al., 2019).

[‡]This chapter is based on Goodell, J. W., Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters*, 36, 101578, <https://doi.org/10.1016/j.frl.2020.101578>.

It remains to be seen what changes COVID-19 will eventually bring to individuals, societies, and, to industries. There is already a flurry of academic interest in all aspects and implications of the COVID crisis (Richard and Beatrice, 2020; Goodell, 2020). Academics are already addressing possible ways of mitigating economic damage¹ (Gopinath, 2020); how markets will react and how markets have already suggested impacts² (Ramelli and Wagner, 2020). One early step in this process is to investigate market expectations of COVID-19's impact across industries. As has long been noted (Schwert, 1981), stock markets can offer insights into investor expectations. There is now particular attention on how recent market reactions may reflect economic expectations (Ramelli and Wagner, 2020). There is a great deal of literature on shocks impacting economies and markets. Particularly, oil shocks (Aggarwal, Akhigbe, and Mohanty, 2012; Elyasiani, Mansur, and Odusami, 2011; Nandha and Faff, 2008; Sakaki, 2019; Zavadzka, Morales, and Coughlan, 2020; Wang, Wu, and Yang, 2013; You et al., 2017); monetary transmissions (Ammer, Vega, and Wongswan, 2010; Bredin et al., 2009); and industrial accidents (Corbet et al., 2020b)³.

As noted by Goodell (2020), COVID-19 presents a new normal for investors. The extent of global impact, along with the likelihood of future occurrences; as well as the likelihood of survivability (compared to other catastrophe scenarios) suggests the next time there is a sudden appearance of a contagious respiratory illness, or a new flaring of COVID-19, there will concomitantly be substantial financial market reaction. COVID-19 will shape future investigations of financial markets. It is important to understand how the unprecedented social distancing that has ensued from this enormous global event has impacted industries and the financial market.

We consider whether the legislator trades in question were in a time window that would be consistent with trading ahead of the market. Did the trades occur before abnormal returns in particular industries that were identifiable with COVID? Toward this end, we assess the reactions of US industries to sudden COVID-related news announcements, concomitantly with an analysis of levels of investor attention to COVID. We analyze the abnormal returns of 49 industrial sectors from December 9, 2019–February 28, 2020, examining the market reactions of US industries to several key US-relevant COVID news announcements through an event study methodology (MacKinlay, 1997). Alternatively, we also examine the impact on industry returns of investor attention, via examining levels of COVID-related Google search term activity (Da, Engelberg, and Gao, 2011).

We find that, post January 21, 2020, there was considerable public attention in the US on COVID-19. Further, for January 21–February 28 levels of this attention are associated with returns in several industries that are also later associated with abnormal

¹See Abu-Ghunmi, Corbet, and Larkin (2020), Adda (2016), and Zhu, Gao, and Sherman (2020).

²Including the impacts of subjective reactions (see Flori (2019)).

³See also (Evans and Elphick, 2005; Wu, 2019) for systemic risks in general.

returns around a February 26 COVID-related news announcement. Second, we analyze more specifically the market reactions to three notable news releases: 1) the first US confirmed cases (January 20, 2020); 2) the Public Health Emergency of International Concern announcement (January 30, 2020); and 3) the first local transmission case (February 26, 2020)⁴. Overall, we find little evidence of abnormal returns until February 26, 2020. Results suggest that, at an industry-level, for legislator trading to be “ahead of the market” it needed to have been done prior to February 26, and involving the 15 industries we identify as having abnormal returns, especially medical and pharmaceutical products (positive); restaurants, hotels, and motels (negative); as well as services and utilities. These criteria are met by many of the legislator trades. Our results help to both parameterize concerns about this case of legislator trading; as well as provide insight into the reactions and expectations of investors toward COVID-19.

3.2 Data and methodology

3.2.1 Data

This study covers the daily stock return of 49 industries in the United States, following the Ken French portfolio taxonomy. Industry portfolios are constructed by assigning each NYSE, AMEX and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. COMPUSTAT SIC codes are used, with alternative CRSP SIC codes when necessary. To gauge general market performance, we utilize the S&P 500 Composite Index because it includes the largest market capitalization on the NYSE and NASDAQ. We calculate as the natural logarithmic first difference of the daily closing prices for the market index. Table 3.1 lists summary statistics for US industry for our period of study.

3.2.2 Methodology

Google searches and industry returns

We use the Google search term “corona” as a proxy to examine the impact of investor attention on industry stock return⁵. Following Edmans, Garcia, and Norli (2007), we examine the impact of investor attention on the abnormal returns, measured by the “raw residual” in the conventional CAPM model. We estimate:

$$R_{it} = \widehat{\alpha}_i + \widehat{\beta}_i R_{mt} + \epsilon_{it} \quad (3.1)$$

⁴“CDC Confirms Possible Instance of Community Spread of COVID-19 in U.S”.

⁵We do not use the term “COVID-19” because the World Health Organization changed the name of “SARS-CoV-2” to “COVID-19” after February 12, 2020, while our investigation includes the longer period from December 9, 2019 to February 28, 2020. Additionally, we find, over the period of our investigation, a much greater prevalence of search-term hits on “corona” than on “COVID-19.” The Appendix highlights that while “corona” tended to capture clearer evidence about investor attention than “COVID-19.”

TABLE 3.1: Descriptive statistics of 49 industries, market, and Corona attention

No	Variable	Mean	Std. Dev.	Skewness	Kurtosis
1	Agriculture	0.08	1.93	-0.49	4.48
2	Food Products	-0.16	0.88	-0.74	5.34
3	Candy and Soda	-0.02	1.03	-1.43	8.81
4	Beer and Liquor	-0.07	1.01	-1.91	8.02
5	Tobacco Products	-0.14	1.16	-1.41	6.75
6	Creation	-0.35	1.54	-0.46	2.99
7	Entertainment	0.06	1.55	-0.48	3.11
8	Printing and Publishing	-0.16	1.42	-0.08	4.65
9	Consumer Goods	-0.12	0.95	-2.29	10.72
10	Apparel	-0.18	1.23	-1.32	5.71
11	Healthcare	-0.06	1.13	-0.71	3.95
12	Medical Equipment	-0.14	1.05	-0.91	3.68
13	Pharmaceutical Products	-0.07	0.91	-1.16	5.45
14	Chemicals	-0.30	1.34	-1.13	5.05
15	Rubber and Plastic Products	-0.16	1.08	-0.85	4.13
16	Textiles	-0.28	1.66	-0.17	2.71
17	Construction Materials	-0.15	1.14	-1.05	4.28
18	Construction	-0.07	1.29	-1.01	4.77
19	Steel Works Etc	-0.52	1.42	-0.67	3.65
20	Fabricated Products	-0.13	1.89	-0.55	3.28
21	Machinery	-0.11	1.36	-0.63	4.04
22	Electrical Equipment	-0.13	1.26	-0.79	5.26
23	Automobiles and Trucks	0.20	2.53	-0.30	6.25
24	Aircraft	-0.29	1.36	-1.20	5.71
25	Shipbuilding, Railroad Equipment	-0.23	1.43	-0.39	3.15
26	Defense	-0.04	1.34	-0.89	5.41
27	Precious Metals	0.16	1.72	-0.95	5.43
28	Non-Metallic and Industrial Metal Mining	-0.28	1.55	-0.52	3.09
29	Coal	-0.60	2.95	1.18	6.29
30	Petroleum and Natural Gas	-0.44	1.69	-0.73	4.93
31	Utilities	-0.03	1.01	-2.40	10.31
32	Communication	-0.13	0.92	-1.32	5.49
33	Personal Services	-0.12	1.04	-1.47	5.58
34	Business Services	-0.06	1.10	-1.56	6.18
35	Computers	-0.14	1.49	-0.92	4.07
36	Computer Software	0.04	1.28	-1.62	6.75
37	Electronic Equipment	0.01	1.64	-1.44	5.4
38	Measuring and Control Equipment	-0.16	1.17	-1.29	4.75
39	Business Supplies	-0.22	1.01	-0.46	4.51
40	Shipping Containers	-0.12	1.34	-0.93	5.42
41	Transportation	-0.17	1.30	-1.56	5.74
42	Wholesale	-0.20	1.05	-1.55	6.15
43	Retail	-0.04	1.01	-1.75	8.02
44	Restaurants, Hotels, Motels	-0.11	1.06	-1.46	5.51
45	Banking	-0.23	1.28	-1.49	5.96
46	Insurance	-0.16	1.30	-1.22	6.78
47	Real Estate	-0.15	1.13	-1.24	5.59
48	Trading	-0.14	1.16	-1.18	4.76
49	Almost Nothing	-0.11	1.03	-1.44	6.39
50	Market return	-0.11	1.07	-2.16	8.65
51	Δ Corona	0.06	0.24	0.69	4.57

Note: Our sample covers the period from December 9, 2019 to February 28, 2020. Values are in % for US Industries.

where R_{it} represents the return of a specific industry i on day t which belongs to the estimation window, R_{mt} is the market return of the United States market on day t belonging to the same period, and ϵ_{it} is an abnormal raw return, which is not captured by the Capital Asset Pricing Model (CAPM). We subsequently employ Ordinary Least Squares (OLS) to estimate $\hat{\beta}_A$ from:

$$\epsilon_{it} = \beta_0 + \beta_A \text{Attention} + \beta_D \text{Dummy} + \mu_{it} \quad (3.2)$$

where μ_{it} is an error term that can be heteroskedastic and contemporaneously correlated across industries. The delta of attention represents the change in the standardized Google search term in the specific period from December 9, 2019 to February 28, 2020. In addition, “dummy” is a binary variable receiving ‘0’ if return is before January 21, 2020th—the first confirmed case in the United States and ‘1’ otherwise ⁶.

Event study

We subsequently employ an event-study methodology to identify abnormal returns. We choose an estimation window of 250 trading days, excluding the 14 days preceding the event. Table 3.2 summarizes our event timeline for three events. We estimate the expected return for each industry with a market model.

TABLE 3.2: Summary of event, estimation window and excluded days

No	Event	Estimation window
1	The first confirmed case (1/20/2020)	January 02, 2019 - December 27, 2020
2	PHEIC (1/30/2020)	January 11, 2019 - January 08, 2020
3	The first domestic local transmission February 26, 2020	February 07, 2019 - February 04, 2020

Note: Following (MacKinlay, 1997). All events excluded 14 days. PHEIC represents the Public Health Emergency of International Concern.

$$R_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt} + \epsilon_{it} \quad (3.3)$$

In Equation 3.3, R_{it} represents the return of a specific industry i on day t which belongs to the estimation window, R_{mt} is the market return of the United States market on day t belonging to the same period. α_i and β_i are parameters in the regression for constant terms and coefficients, respectively. The expected return $E(R_{it})$ is calculated as follows:

$$E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{mt} \quad (3.4)$$

Abnormal returns are estimated as follows:

$$AR_{it} = R_{it} - E(R_{it}) \quad (3.5)$$

⁶See Appendix figure B.1 - B.3 for illustration of correlations of industries and Google searches over several sampling periods.

In Equation 3.5, AR_{it} denotes the abnormal return of one industry return on day t , which belongs to event window. To measure the total impact of an event over a particular period, we sequentially add up the individual abnormal returns to create a cumulative abnormal return (CAR) for each of the event windows. Due to data availability, we perform $[-2, 2]$ and $[0, 2]$ for the first domestic local transmission on February 26, 2020. The other events are followed by longer event windows $[3,3]$, $[0,3]$ to examine persistent effects.

$$CAR_{it} = \sum_{t=t_1}^{t_2} AR_{it} \quad (3.6)$$

In Equation 3.6, t_1 and t_2 represent the start and end of event window. After constructing AR_{it} and CAR, we perform t-tests to examine whether the ARs and CARs are different from zero.

3.3 Results

3.3.1 When did investor interest in COVID begin?

Figure 3.1 highlights the levels of investor attention (proxied by levels of Google searches on ‘corona’ by date). On January 21, there occurs the first strong indication of investor attention, as illustrated by the figure.

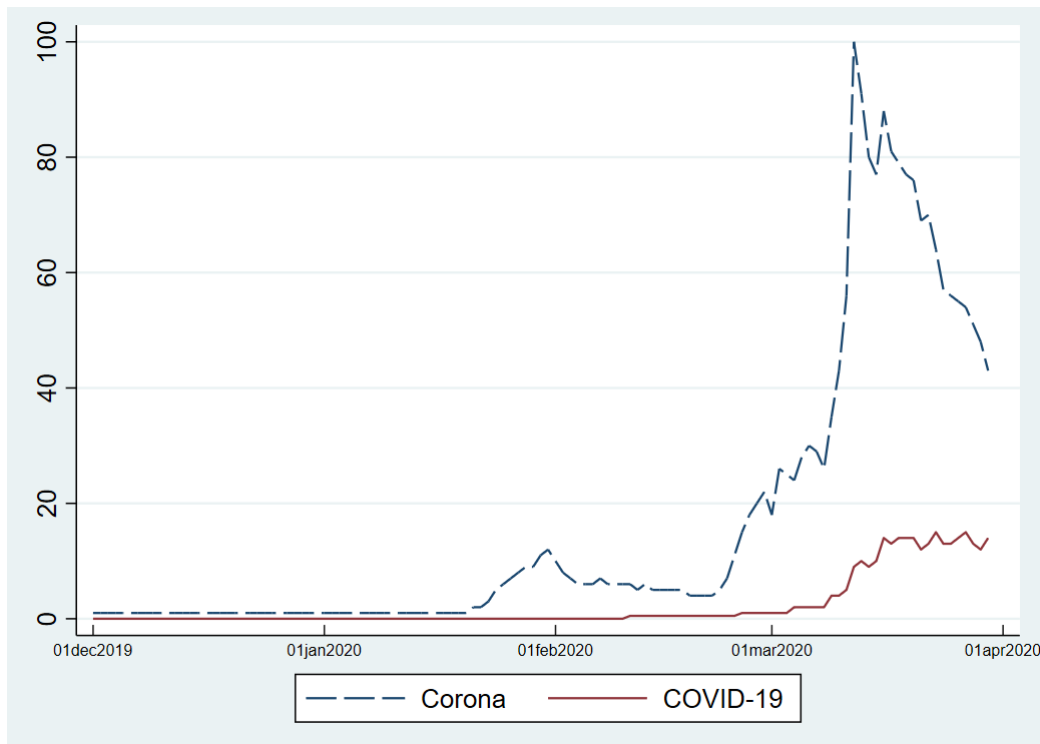


FIGURE 3.1: The time varying of Corona and COVID-19 searching terms in the US.

3.3.2 Impact of COVID-related investor attention

We consider the impact of investors' attention on specific industries by three main sub-categories: (i) full sample, (ii) before January 21, 2020, and (iii) after January 21, 2020. Table 3.3 summarizes OLS regressions for the impact of the Google search term 'corona' on 49 US industries⁷. Several key features of the role of investors' attention are worth highlighting. First, only four industries had significant coefficients before the day when the US had the first confirmed case⁸. Interestingly, the returns of the communication industry had a positive association (significant at 5%) with an increase in Google searches about corona prior to January 21, 2020. Perhaps investors were predicting social-distancing related growth in the communication industry?

Returns to entertainment, heavy industry (including steel, chemical, construction materials, machinery, electrical equipment, industrial metal mining, and coal), and services (including restaurants, hotels, motels; and insurance) are negatively associated with investors were paying more attention to the coronavirus. These results are intuitively consistent with these industries likely to face difficulties with importing and exporting the materials from China.

While evidence of past research is mixed with whether Google search terms can predict abnormal returns (e.g., Donadelli and Gerotto (2019), Kim et al. (2019), and Swamy, Dharani, and Takeda (2019)), we evidence that levels of searches on "corona" had an association with industry-level returns⁹. The results of this section help confirm that our results outlined in the next section for the abnormal returns associated with three key COVID-related news announcements are indeed reactions to concern about COVID-19.

3.3.3 Abnormal returns

Table 3.4 demonstrates the abnormal return in the first column on February 26, 2020, representing the first domestic case confirmed in California with no travel history. We evidence 15 US industries' returns reacting to this news. Except for tobacco, all industries exhibited a negative abnormal return on this day¹⁰. We also find three primary industries, namely precious metals, utilities; and restaurants, hotels, motels, experienced both abnormal return from the first domestic COVID-19 confirmed case, but also cumulative average abnormal returns in the event window $[0, 2]$, consistent with

⁷Because of the notable change in investor attention on January 21, Table 3.3 presents results for three different samples: 1) the full-sample period; 2) before January 21; and 3) after January 21.

⁸Construction materials and computer software industries exhibited a weak decline in abnormal return when investors paid more attention to coronavirus. Perhaps COVID-related disruption in trading activities of these materials led to a decrease in stock return due to the potential loss in the expected future cash flow. Electronic and construction materials are top trading sectors between the US and China (Burggraf, Fendel, and Huynh, 2020).

⁹See also Broadstock and Zhang (2019); as well as Philippas et al. (2019).

¹⁰We only observe the positive abnormal return for tobacco on one day. February 26, 2020 was the first day that several tobacco companies in the US, implemented price increases, possibly engendering expectations of higher future cash flows.

TABLE 3.3: The impact of public focus on ‘corona’ on industry returns

Industry	Δ Corona			Industry	Δ Corona		
	Full sample	After 21-Jan	Before 21-Jan		Full sample	After 21-Jan	Before 21-Jan
Agriculture	-0.707 [-0.748]	-1.394 [-1.47]	0.857 [0.391]	Defense	0.737 [1.36]	1.445** [2.874]	-0.814 [-0.722]
Food Products	0.414 [1.466]	0.338 [1.266]	1.086 [1.248]	Precious Metals	0.249 [0.319]	0.268 [0.295]	0.342 [0.166]
Candy & Soda	0.524* [1.917]	0.607** [2.45]	0.323 [0.394]	Non-Metallic Mining	-1.196 [-2.381]	-1.446** [-2.599]	-0.089 [-0.08]
Beer & Liquor	0.561* [1.856]	0.692*** [3.486]	0.2 [0.164]	Coal	-2.973** [-2.076]	-3.329* [-1.745]	-1.565 [-0.616]
Tobacco Products	0.07 [0.128]	0.436 [0.717]	-0.529 [-0.647]	Petroleum and Gas	-0.315 [-0.425]	-0.573 [-0.58]	1.115 [0.94]
Creation	0.329 [0.503]	0.482 [0.53]	0.525 [0.493]	Utilities	0.555 [1.569]	0.571 [1.539]	0.955 [0.962]
Entertainment	-0.932 [-1.649]	-1.363** [-2.236]	0.063 [0.079]	Communication	0.258 [1.115]	0.099 [0.309]	0.858** [3.052]
Printing and Publishing	-0.656 [-1.363]	-0.947 [-1.541]	0.411 [0.494]	Personal Services	-0.831* [-1.975]	-0.844 [-1.581]	-0.513 [-0.973]
Consumer Goods	0.124 [0.402]	0.076 [0.253]	0.336 [0.404]	Business Services	-0.204 [-0.735]	-0.149 [-0.423]	-0.562 [-1.677]
Apparel	-0.472* [-1.703]	-0.667 [-1.69]	0.515 [1.176]	Computers	-0.592* [-1.884]	-0.332 [-0.908]	-1.021 [-1.434]
Healthcare	-0.182 [-0.542]	-0.343 [-0.862]	0.252 [0.374]	Computer Software	-0.297 [-1.028]	-0.258 [-0.643]	-0.752* [-1.727]
Medical Equipment	0.026 [0.08]	0.079 [0.178]	-0.053 [-0.196]	Electronic Equipment	0.406 [0.971]	0.616 [1.21]	-0.185 [-0.249]
Pharmaceutical Products	-0.198 [-0.547]	-0.265 [-0.615]	0.145 [0.185]	Measuring control tool	-0.24 [-1.147]	-0.412* [-1.727]	0.533 [1.265]
Chemicals	-0.315 [-0.772]	-0.787* [-1.95]	1.169 [1.349]	Business Supplies	-0.239 [-0.688]	-0.277 [-0.692]	0.64 [0.907]
Rubber, Plastic Products	-0.393 [-0.917]	-0.515 [-1.037]	0.43 [0.545]	Shipping Containers	0.033 [0.053]	-0.13 [-0.169]	0.356 [0.352]
Textiles	-0.274 [-0.396]	-0.51 [-0.702]	0.455 [0.208]	Transportation	-0.48 [-1.406]	-0.683* [-1.717]	0.381 [0.582]
Construction Materials	-0.651** [-2.257]	-0.702* [-1.901]	-0.592* [-2.028]	Wholesale	0.137 [0.499]	0.139 [0.415]	0.279 [0.417]
Construction	0.267 [0.446]	0.038 [0.052]	1.122 [1.027]	Retail	0.136 [0.478]	0.006 [0.015]	0.131 [0.281]
Steel Works Etc.	-0.756 [-1.154]	-1.659** [-2.404]	1.917* [1.928]	Restaurants, Hotels	-0.644** [-2.277]	-0.665* [-1.89]	-0.438 [-0.979]
Fabricated Products	-1.164 [-1.34]	-0.851 [-0.765]	-1.351 [-1.085]	Banking	-0.241 [-1.081]	-0.292 [-1.234]	-0.163 [-0.327]
Machinery	-0.391 [-1.41]	-0.662* [-1.852]	0.273 [0.605]	Insurance	-0.353 [-1.278]	-0.371* [-1.002]	-0.487 [-0.86]
Electrical Equipment	-0.393 [-1.58]	-0.698** [-2.27]	-0.018 [-0.044]	Real Estate	-0.492 [-1.308]	-0.711 [-1.749]	0.173 [0.232]
Automobiles and Trucks	-0.569 [-0.367]	-1.286 [-0.571]	0.421 [0.328]	Trading	-0.027 [-0.135]	0.15 [0.627]	-0.527 [-1.191]
Aircraft	0.184 [0.375]	0.149 [0.265]	-0.093 [-0.084]	Almost Nothing	-0.069 [-0.24]	-0.038 [-0.094]	-0.273 [-0.681]
Shipbuilding, Railroad	-0.658 [-1.587]	-0.753 [-1.571]	-0.128 [-0.121]				

Note: * < 0.1, ** < 0.05, *** < 0.01. T-statistics are in the bracket. There are 49 industries in three period such as the full sample (December 9, 2019 to February 28, 2020), before the first case (December 9, 2019 to January 21, 2020), after the first case (January 21, 2020 to February 28, 2020).

a delayed market reaction. However, the event window $[-2, 2]$ of these sectors has a downward trend, consistent with the market processing previous information about COVID-19 before the first domestic confirmation. We also weakly evidence for medical equipment and pharmaceutical products a positive abnormal return in the event window $[-2, 2]$, consistent with evolving investor expectations about the potential profit from these industries in the pandemic.

There are three main conclusions regarding US industries' reaction in the first domestic case confirmed. First, effects happened quite strongly on this event date, with thirty percent of all industries having a negative abnormal return. Notably, services and utilities had the most sensitive reaction, while a particularly positive outlook was in medical and pharmaceutical products. Restaurants, hotels, and motels; as well as utilities, experienced negative reactions. Of particular interest for this paper, the transportation industry, which includes airlines and cruise lines, had a significantly negative abnormal return on February 26. However, this effect was not persistent, with the CARs not significant. We also calculated abnormal returns and cumulative abnormal returns on two other dates: 1) the first US confirmed cases (January 20, 2020); and 2), the Public Health Emergency of International Concern announcement (January 30, 2020). However, perhaps surprisingly, the market was without any reaction on these dates. Overall, results strongly suggest that the market did not react to the COVID-19 crisis until February 26, 2020. Therefore, the trades made by legislators prior to February 26 are consistent with being ahead of the market.

3.4 Conclusion

During the ongoing COVID-19 pandemic in the US, there has been considerable public and media attention regarding several US legislators who traded stocks from late January through February 2020. The concern is that these legislators traded in anticipation of COVID-19 having a major impact on the financial markets, while publicly suggesting otherwise. We consider whether these legislator trades were in a time window that would be consistent with trading ahead of the market. Towards this end, we assess the reactions of US industries to sudden COVID-related news announcements, concomitantly with an analysis of levels of investor attention to COVID. We analyze the abnormal returns of 49 industrial sectors from December 9, 2019 to February 28, 2020, examining the market reactions of US industries to several key US-relevant COVID news announcements through an event study methodology (MacKinlay, 1997). Alternatively, we also examine the impact on industry returns of investor attention, via examining levels of COVID-related Google search term activity (Da, Engelberg, and Gao, 2011).

TABLE 3.4: The ARs and CARs across industries on February 26, 2020

No	Industry	Window [0]		Window [-2, 2]		Window [0, 2]	
		AR	T-stats	CAR	T-stats	CAR	T-stats
1	Agriculture	-0.007	-0.875	0.038	1.126	0.004	0.117
2	Food Products	-0.011	-1.999**	-0.027	-1.142	-0.028	-1.208
3	Candy & Soda	-0.012	-0.721	-0.040	-0.579	-0.021	-0.302
4	Beer & Liquor	-0.015	-1.098	-0.007	-0.124	-0.024	-0.419
5	Tobacco Products	0.045	2.983***	0.037	0.591	0.059	0.958
6	Creation	-0.020	-2.001**	0.021	0.504	0.000	0.010
7	Entertainment	-0.030	-4.097***	-0.054	-1.7742*	-0.017	-0.553
8	Printing and Publishing	-0.017	-1.107	-0.010	-0.162	0.003	0.056
9	Consumer Goods	-0.010	-1.717*	0.002	0.064	0.010	0.389
10	Apparel	-0.007	-0.804	0.025	0.720	0.024	0.684
11	Healthcare	-0.010	-1.027	-0.002	-0.064	0.000	-0.006
12	Medical Equipment	-0.004	-0.484	0.061	1.708*	0.046	1.302
13	Pharmaceutical Products	-0.001	-0.112	0.067	1.651*	0.050	1.245
14	Chemicals	-0.008	-0.969	0.007	0.218	0.011	0.350
15	Rubber and Plastic Products	0.003	0.248	0.057	1.060	0.054	1.000
16	Textiles	-0.005	-0.345	-0.023	-0.403	-0.022	-0.375
17	Construction Materials	-0.014	-1.862*	0.005	0.177	-0.002	-0.057
18	Construction	-0.027	-3.162***	-0.039	-1.085	-0.028	-0.778
19	Steel Works Etc	-0.008	-0.698	0.062	1.402	0.033	0.750
20	Fabricated Products	-0.012	-0.948	0.057	1.107	0.044	0.861
21	Machinery	-0.005	-0.677	0.040	1.267	0.025	0.813
22	Electrical Equipment	-0.009	-1.008	0.004	0.118	-0.004	-0.099
23	Automobiles and Trucks	-0.009	-0.860	0.014	0.312	0.015	0.338
24	Aircraft	-0.018	-2.347**	-0.049	-1.554	-0.019	-0.608
25	Shipbuilding, Railroad Equipment	-0.007	-0.546	0.049	0.953	0.035	0.681
26	Defense	-0.005	-0.477	-0.008	-0.181	0.003	0.056
27	Precious Metals	0.017	0.753	-0.349	-3.696***	-0.203	-2.152**
28	Non-Metallic and Industrial Metal Mining	-0.004	-0.333	-0.016	-0.306	-0.001	-0.025
29	Coal	-0.046	-2.471**	0.174	2.2907**	0.124	1.636
30	Petroleum and Natural Gas	-0.031	-1.591	0.022	0.269	0.016	0.196
31	Utilities	-0.014	-2.368**	-0.084	-3.540***	-0.069	-2.926***
32	Communication	-0.013	-1.528	0.014	0.394	0.001	0.040
33	Personal Services	-0.019	-2.549**	-0.001	-0.037	0.001	0.033
34	Business Services	-0.010	-2.139**	-0.004	-0.235	-0.004	-0.209
35	Computers	-0.021	-2.679***	-0.007	-0.218	-0.006	-0.192
36	Computer Software	-0.002	-0.399	0.031	1.344	0.021	0.906
37	Electronic Equipment	-0.012	-1.885*	0.031	1.135	0.014	0.519
38	Measuring and Control Equipment	0.001	0.180	0.023	0.942	0.028	1.144
39	Business Supplies	-0.009	-0.920	0.011	0.297	0.009	0.247
40	Shipping Containers	0.009	0.982	-0.009	-0.240	0.011	0.290
41	Transportation	-0.020	-2.460**	-0.008	-0.246	0.003	0.078
42	Wholesale	0.002	0.365	0.033	1.248	0.029	1.116
43	Retail	-0.015	-1.614	0.009	0.235	0.005	0.137
44	Restaurants, Hotels, Motels	-0.033	-6.097***	-0.062	-2.772***	-0.051	-2.279**
45	Banking	-0.003	-0.484	-0.003	-0.121	-0.012	-0.499
46	Insurance	-0.007	-1.608	-0.024	-1.438	-0.026	-1.511
47	Real Estate	-0.018	-2.437**	-0.024	-0.806	-0.031	-1.022
48	Trading	-0.005	-0.985	0.015	0.659	-0.004	-0.165
49	Almost Nothing	-0.005	-0.725	-0.002	-0.081	-0.003	-0.095

Note: This table represents the cumulative average abnormal returns for 49 industries in the American market. CAR demonstrates the cross-sectional average of CAR returns over industry indices obtained for different event windows. We test the null hypothesis of $H_0: CAR = 0$ with the t-statistics and *, **, *** denote for the significance level at 10%, 5%, and 1%, respectively.

We find that, post January 21, there was considerable public attention in the US on COVID-19. Further, for January 21–February 28 levels of this attention are associated with returns in several industries that are also later associated with abnormal returns around a February 26 COVID-related news announcement. Second, we analyze more specifically the market reactions to three notable news releases: 1) the first US confirmed cases (January 20, 2020); 2), the Public Health Emergency of International Concern announcement (January 30, 2020); and 3) the first local transmission case (February 26, 2020). Overall, we find little evidence of abnormal returns until February 26, 2020. Results suggest that, at an industry-level, for legislator trading to be “ahead of the market” it needed to have been done prior to February 26, and involving the 15 industries we identify as having abnormal returns, especially medical and pharmaceutical products (positive); restaurants, hotels, and motels (negative); as well as services and utilities. These criteria are met by many of the legislator trades.

Regarding the movement of industries with Google search activity, we find that an increase of one percentage point in the search term would predict a 0.651% decrease in construction material returns over the period from December 9, 2019 to February 28, 2020. As Google searches on corona in the US were increasing rapidly, this is consistent with there being a significant economic benefit of trading prior to February 26 (our abnormal return announcement date) in this industry.

In summary, our results help to parameterize concerns about this case of legislator trading; as well as provide insight into the reactions and expectations of investors toward COVID-19. We assist policymakers to identify industries that had COVID-related abnormal returns. We identify that trading ahead of the market in these industries would be economically meaningful. We also identify particularly February 26, 2020 as a key date with regards to general US market reaction to COVID-19. This is the date that the US Centers for Disease Control and Prevention (CDC) announced a possible first community transmission of COVID-19 in the US¹¹. This information will be of interest to policymakers interested in the reactions and trading of various market actors to COVID-19.

There has been already much ongoing interest in the impact of global economic shocks on industries. The COVID-19 crisis, with its perhaps unprecedented global reach and scale will no doubt prompt a great deal of future research in this area (Goodell, 2020). This paper presents one of the first analyses of how investors react to the news announcement regarding the COVID-19 at the industry level.

¹¹CDC Confirms Possible Instance of Community Spread of COVID-19 in U.S.

Chapter 4

Gold, platinum, and expected Bitcoin returns[§]

4.1 Introduction

4.1.1 Background

Gold and Platinum are precious metals¹ that share many unique qualities – they are dense, soft, and malleable metals, perfect for shaping, handling, smelting, and fabricating. However, there is one important thing that differentiates them from each other that has important economic implications. While gold is considered a *consumption good*, which is mainly used in dentistry, in the aerospace industry, and, most commonly, in jewelry and other artistic applications, it is also seen as an investment and a *store of value*² during economic downturns (Bernstein, 2012). Platinum, on the other hand, has important industrial applications, such as catalytic converters for cars and turbine engines for planes, but is rarely considered a store of value. Therefore, the ratio of gold to platinum should cancel out the consumption component and should work as an economic state variable by isolating variation in risk and economic confidence. Bitcoin has been controversially known as the ‘Digital Gold’³ since many studies indicated Bitcoin features as superior resilience during the period of financial distress. When it comes to ‘Digital Gold’, this viewpoint is controversial that many papers have argued about it. Precisely, Popper (2015) argues that Bitcoin is likely to be plausibly component in the optimal portfolio to avoid the economic crisis or the gradually losing currencies’ values. In contrast, Chibane and Janson (2020) and Klein, Thu, and Walther (2018) criticized that Bitcoin does not reflect any distinctive properties of gold. In particular, investors flock to Bitcoin market to as safe-haven but the level of geopolitical risk is quite low. Thus, these behaviors are just speculation. To sum up,

[§]This chapter is based on Huynh, T. L. D., Burggraf, T., Wang, M. (2020). Gold, platinum, and expected Bitcoin returns. *Journal of Multinational Financial Management*, 56, 100628, <https://doi.org/10.1016/j.mulfin.2020.100628>.

¹A precious metal is a rare, naturally occurring metallic chemical element of high economic value.

²Brennan (1976) and Fama and French (1988) also concluded that gold has different storage costs for precious metals because gold seems unresponsive.

³This point does not only result from academia research but also industry perspectives. The term of digital gold refers to the detachment from centralized mechanism of government, which allows people and investors to preserve wealth in a secure way.

the property of using Bitcoin as Digital gold is still ongoing debatable. Although Bitcoin has a controversial function in terms of the global financial crisis 2008, Dyrberg (2016b) draws attention that Bitcoin gained the popularity in investing world as well as strengthened its value although Baur, Dimpfl, and Kuck (2018) found that Bitcoin has distinctive characteristics in terms of return, volatility and correlation with gold and US dollar. It also implies the controversial features of Bitcoin, which is still attracting scholars' attention. In the same vein, Bouri et al. (2017) use the dynamic conditional correlations to draw a conclusion that Bitcoin is likely to be good shelter for the uncertain shakes in banking and financial system. Unexpectedly, Luther and Salter (2017) witnesses the shifting movement from deposit balances to Bitcoin by depositors during the Cyprus bailout. This effect is also consistent with the previous study of Luther and Olson (2013) that investors tend to move to Bitcoin when there is uncertainty in the Euro-area. Meanwhile, Bouoiyour and Selmi (2017) argue that Bitcoin is considered as one of appealing options to hold cash when several governments (Venezuela and India) imposed the law regarding the restriction of capital outside. Therefore, Bitcoin could be an alternative tool for people to hold. Gradually, this results in the comparison between Bitcoin and gold. Thus, Bitcoin is possibly considered as the safe-haven like gold during the economic bailout or financial distress. However, 'is Bitcoin safe-haven?' is still an open question because of its complex characteristics while the use of gold in times of severe distress was mentioned many times ago.

4.1.2 Motivation

While there is mounting literature to confirm the predictive power of Gold-Platinum ratio (GP) to equity markets (Huang and Kilic, 2019), bond prices (Bouri, Wohar, et al., 2019), this paper examines the ratio of two precious metals in forecasting Bitcoin returns. The fundamental concept of these two metals as a predictive tool is based on the countercyclical of business. However, we believe that investors use precious metals as alternative hedging instruments in their portfolio due to the lower correlation (Reboredo and Rivera-Castro, 2014; Shahzad et al., 2019a; Baur and McDermott, 2010). Although Bitcoin has just been established in late 2009, one of its distinguishing features is its resilience during financial turmoil, underlining Bitcoin as a hedging or safe-haven instrument during financial distress (Bouri and Dyrberg, 2016; Bouri et al., 2017; Bouri, Wohar, et al., 2019; Corbet et al., 2018; Bouoiyour, Selmi, and Wohar, 2018; Selmi et al., 2018). Hence, apart from its investing and hedging function, this paper examines the role of gold as a predictive tool. This paper contributes to the literature on Bitcoin return predictability. While previous studies examine the causal relation between Bitcoin and supply and demand (Ciaian, Rajcaniova, and Kancs, 2016), return and volatility (Balcilar and Roubaud, 2017), or investor sentiment (Burggraf et al., 2019; Kristoufek, 2013) to the best of our knowledge, this is the first study to link precious metals and GP to cryptocurrencies. By demonstrating that the ratio of gold to platinum prices (GP) has predictive power, our work also extends the growing literature on the role of GP in predict financial assets. Moreover, the current literature

examines the relationship between gold and Bitcoin by using advanced autoregressive distributed lag (ARDL) models (Bouri, Lahiani, and Shahbaz, 2018; Klein, Thu, and Walther, 2018), or wavelet analysis (Kang, McIver, and Hernandez, 2019). However, this paper revisits the relationship between Bitcoin and gold returns by taking into account that the movement of two assets involves heterogeneous agents and different time horizons, as well as operates in different time scales. More importantly, this study also considers the predictability of GP on Bitcoin excess return, which reflects the opportunity cost in investing the alternative investments with the increase in aggregate market risk, representing the variation of log GP.

This paper will contribute to the existing literature by three main ways. First, our work draws the literature examining the correlation between Gold-Platinum and Bitcoin returns by using Wavelet multiple correlation method, which indicates the different time-scale as well as cyclical movements. The main advantage by using Wavelet Multiple Correlation method is to consider multivariate time series, which allows us consider the randomness of time-series. In addition, this method can handle any sample size with small scale, which represents in our data as monthly from 2013 to 2019. Second, using the simple regression and rolling in one-three-six months, this paper investigates the role of Gold-Platinum on predicting Bitcoin return. Third, checking robustness by two methods such as quantile regression and sub-sample with the new year, we find that the ratio of Gold-Platinum is still robust when it predicts the Bitcoin return. In the following part, we will summarize our main methodology, applied in our empirical part. The rest of this study is structured as follows. Section 4.2 reviews the existing literature regarding Bitcoin and gold. Section 4.3 provides the data used in this study and introduces wavelet multiple correlation and quantile regression. Section 4.4 discusses the results. Section 4.5 concludes.

4.2 Literature Review

The growing bodies of literature regarding gold and Bitcoin open many different perspectives rather than their functions. What are the similarities and differences between Gold and Bitcoin? Bhaskar, Linacre, and Machin (2017) argue that Bitcoin should be intangible asset with many ambiguity regarding legal issues while gold offer the clear picture of tangibility, historical and intrinsic value as well as acceptance for global monetary reserve. By doing so, Kristoufek (2015) and Ciaian, Rajcaniova, and Kancs (2016) confirm that Bitcoin possesses the unique characteristic which qualifies the standards of financial and speculative assets. Latter, Kristoufek (2018) claims that Bitcoin is still considered as the shallow market, which is not attractive for big institutional investors while Xu and Zhang (2019) support the hypothesis that institutional players are occupied by the majority in gold market. Interestingly, both of these assets are classified as commodity asset by the US Commodity Futures Trading Commission (Shahzad et al., 2019b) although the process of gold mining and Bitcoin mining is totally different

(Bouri et al., 2017; Tufano, 1996). While gold is based on physical mining production, Bitcoin is linked to Graphics Processing Units (GPU) for mining new unit of Bitcoin. Thus, both gold and Bitcoin are not easily produced, which immediately pressures on the supply source. Furthermore, Shahzad et al. (2019b) emphasize that these assets are less sensitive to positive and negative news and they do not have any ability to generate the future cash-flows like the conventional financial assets such as stock or fixed-income instrument. Thus, Shahzad et al. (2019b) suggest that both of them are good at hedging inflation as well as stock market risk due to these aforementioned characteristics. This study also points out one of interesting features regarding inflation. It means Bitcoin has circulating supply, known as coherent algorithm; therefore, the number of Bitcoin unit could not be increased by inflationary ‘money printing’. Following this argument, Kristoufek (2015) indicates that the combination of Bitcoin and gold will be very effective for diversification. However, there is no previous study mentioned that the ratio of Gold and Platinum is also a tool for predicting Bitcoin return. Hence, this paper will bridge this gap by using the previous study of Huang and Kilic (2019) to construct Bitcoin pricing model with gold as the main component.

The study of Gomes, Kogan, and Yogo (2009) implies that the shocks in the precious metals market might not influence the stock’s risk premium. Afterwards, Huang and Kilic (2019) built the theoretical framework to prove that both gold and platinum decline when the probability of financial turmoil increases. This study also confirms that gold prices decrease less relative than platinum. Therefore, this ratio Gold-Platinum could predict the stock return due to the co-integration of Gold prices and Platinum prices in terms of the dynamic movement (Huang and Kilic, 2019)⁴. Recently, Syed Zwick and Syed (2019) use Gold as the predictive tool to forecast Bitcoin return by using the threshold regression model. This study also indicates that an increase in gold price might positively predict the Bitcoin price, which triggers the higher demand for Bitcoin under uncertainties. This study also implies the radical movement as a good diversification and a hedging tool. In the early stage, Das and Kannadhasan (2018) explain the investing choices from investors’ behaviors. Accordingly, the risk-averse investors tend to choose the gold while the speculative taste prefer investing in Bitcoin, which shows the significant but weak evidence.

Why should we consider the ratio of natural logarithm of Gold and Platinum ($\log GP$) as predictive tool for Bitcoin? Because the study of Huang and Kilic (2019) indicates that this proxy represents the countercyclical behavior. Therefore, this ratio could predict the equity return not only in the United States but also in the international stock market. Currently, this factor is outperforming nearly all extant return predictors. More importantly, Huang and Kilic (2019) built the theoretical model to prove that

⁴This paper employs the test of Engle and Granger (1987). In this paper, we also performed three types of Copula including Gaussian, Clayton and Gumbel to test the whole, left-tail, right-tail distribution, respectively. Our result indicate that Gold and Platinum during the research period are normally dependent on the whole distribution (With maximized loglikelihood for Gaussian Copulas is 1940 - highest to choose the most appropriate Copulas - Clayton: 1746 and Gumbel: 1893).

this proxy (log GP) offers the information on variation in the aggregate market risk. In doing so, log GP can be used as variable to reflect the economic state. Latterly, the study of Bouri, Wohar, et al. (2019) drew a conclusion that log GP captures valuable predictive information over the evolution of future interest rates by predicting excess returns on the U.S. Government Bonds. This study implies that the ratio of log GP increases the future short-term interest rate, which requires investors to increase their expected premium in another investing channel. Recently, Wolff and Neugebauer (2019) used Machine learning for the proxy (log GP) in predicting equity return. The economic intuitive explanation results from the reflection on systematic risk (Gao, 2016). Although the characteristics of Bitcoin are still controversial, several studies found that Bitcoin should be considered as the alternative investment since it generates substantial higher risk-adjusted returns (Platanakis and Urquhart, 2019; Matkovskyy et al., 2019; Briere, Oosterlinck, and Szafarz, 2015). Concomitantly, some papers considered that Bitcoin can be classified into asset class in the mature stage (Cheah and Fry, 2015; Koutmos, 2018a; Nadarajah and Chu, 2017). Contradictory, Kajtazi and Moro (2019) confirmed that Bitcoin should be treated as speculative assets rather than as means of payment because Bitcoin is not qualified as the investment grade status (Cheah and Fry, 2015; Urquhart, 2016). In scope of this paper, our hypothesis is that Bitcoin is an investment, which has time-varying ‘discount rates’ (‘risk premium’, and ‘expected return’ also reflect the same meaning)⁵ (Cochrane, 2011). Thus, our hypothesis is that log GP, reflecting the uncertain macroeconomic situation, would capture the Bitcoin expected return. In summary, the linkage between log GP and expected Bitcoin returns could be explained through the expected risk premium, which will be discussed in the our main predictability findings.

After reviewing the current literature, this paper sheds a new light on the Bitcoin predictability model. To our knowledge, there are several factors which show predictive power to Bitcoin return such as evolving return (Khuntia and Pattanayak, 2018; Catania, Grassi, and Ravazzolo, 2019), liquidity (Brauneis and Mestel, 2018), investor sentiment (Eom et al., 2019; Nasir et al., 2019), trading volume (Balcilar and Roubaud, 2017), Bitcoin itself price (Salisu, Isah, and Akanni, 2019), twitter (Shen, Urquhart, and Wang, 2019), risk factor (Trucíos, 2019), etc. This paper contributes a new predictive factor to forecast Bitcoin. Although the paper of Welch and Goyal (2007) shows that some predictor is unstable (or having inferior forecasting performance in sub-sample), we do find that the ratio of Gold-Platinum is robust under sub-sample of January effects. The main reason for us to choose the January effect is due to the gold demand in the new year, which is mentioned in the prior literature as a wealth protection device (Street et al., 2016). Therefore, in the January new year, there is an increase in gold

⁵At the same vein, there are three main perspectives to explain why discount rates are varying such as macroeconomic perspective in the future consumption (Fama and French, 1996), biased behavioral theories from ‘expectation’ and ‘risk’ from biases (Barberis and Thaler, 2003), segmented and intermediated markets from risk sharing among the pool of investors (Gabaix, Krishnamurthy, and Vigneron, 2007), liquidity with asymmetric information reflection (Vayanos and Wang, 2012), efficiency market (Milgrom and Stokey, 1982), etc.

prices, which might make our findings not robust (Qi and Wang, 2013). This paper proves that the ratio of Gold-Platinum is stable for in-sample (new-year month) and out-sample (non-new-year month) because of the change in gold demand during these periods. In addition, this paper also confirms the validity of data sources by using another different data from Bitcoin prices, which are retrieved from Thomson Reuters on *Bitstamp* as suggest in the study of Alexander and Dakos (2020). Consequently, the predictive characteristic of log GP is robust for different data sources and data frequency.

4.3 Methodology

4.3.1 Wavelet multiple correlation

This method produces multiscale multiple correlation of 3 variables (Gold-Platinum ratio, excess Bitcoin return and multivariate normal random variate⁶) with approximate confidence intervals.

Let $X_t = (x_{1t}, x_{2t}, \dots, x_{nt})$ be a multivariate stochastic process and $W_{jt} = (w_{1jt}, w_{2jt}, \dots, w_{nt})$ the wavelet coefficients (denoted as λ_j) retrieved using the maximal overlap discrete wavelet transform (MODWT)⁷ to each respective x_{it} process. (Percival and Walden, 2000; Gençay, Selçuk, and Whitcher, 2001).

Wavelet multiple correlation $\varphi_X(\lambda_j)$ is a single set of multi-scale correlations, obtained from X_t . λ_j is the wavelet scale, having the square root of regression coefficient of determination. Fernández-Macho (2012) also indicates that the coefficient of determination for linear combination of variables w_{ijt} , $i = 1, \dots, n$ is a maximum. Then, $\varphi_X(\lambda_j)$ can be estimated as:

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{\max \text{diag} P_j^{-1}}} \quad (4.1)$$

where P_j is the $n \times n$ correlation matrix of size of W_j and the $\max \text{diag}(\cdot)$ operator selects the highest element in the diagonal of the matrix, extracted from $R_i^2 = 1 - 1\rho^{ii}$ where ρ^{ii} is the i^{th} diagonal element of the inverse of the complete correlation matrix. More precisely, Wavelet multiple correlation can be written as:

$$\varphi_X(\lambda_j) = \text{Corr}(w_{ijt}, \hat{w}_{ijt}) = \frac{\text{Cov}(w_{ijt}, \hat{w}_{ijt})}{\sqrt{\text{Var}(w_{ijt})\text{Var}(\hat{w}_{ijt})}} \quad (4.2)$$

where \hat{w}_{ijt} are the fitted values in the regression of w_{ijt} on the rest of the wavelet coefficients at scale λ_j . More importantly, w_{ijt} will be chosen to maximize $\varphi_X(\lambda_j)$.

⁶This variable is randomly generated by the software.

⁷MODWT is a linear algorithm to filter and transform a series into the coefficient related to variation over a set of scales.

After that, when we add the lag \rightarrow into (Equation 4.2), we have the wavelet multiple cross-correlation (WMCC)⁸:

$$\varphi_X(\lambda_j) = \text{Corr}(w_{ijt}, \hat{w}_{ijt+\tau}) = \frac{\text{Cov}(w_{ijt}\hat{w}_{ijt+\tau})}{\sqrt{\text{Var}(w_{ijt})\text{Var}(\hat{w}_{ijt+\tau})}} \quad (4.3)$$

There are several benefits when applying wavelet multiple correlation to detect correlation (Fernández-Macho, 2012). First, this method provides more robust results and avoids spurious correlation when using normal wavelet within multivariate set. Second, it limits the possibility of type I errors in terms of comparing to the multivariate dataset. Lastly, the interpreted results can be used to predict and examine heterogeneous involvement between the Gold-Platinum ratio and excess Bitcoin return under different time horizons and time scales with random changes.

4.3.2 Quantile regression

The second part of this paper employs quantile regression, based on Koenker and Bassett Jr (1978). The main purpose is to examine the marginal effect of the explanatory asset pricing (Gold-Platinum ratio) across the dependent variable's distribution (the excess Bitcoin return). We briefly describe the methodology of quantile regression.

The conditional quantile regression of dependent variable (Y) in terms of X at quantile $\tau \in (0; 1)$ is a defined function $Q_\tau(Y_i) = X_i\hat{\beta}_\tau$. In which, the parameter $\hat{\beta}_\tau$ ought to be estimated so that we obtain the minimum value of total deviation at quantile τ .

$$\hat{\beta}_\tau = \underset{\beta_\tau}{\text{argmin}} \left\langle \tau \sum_{y_i \geq X_i\hat{\beta}_\tau} (y_i - X_i\hat{\beta}_\tau) + (1 - \tau) \sum_{y_i < X_i\hat{\beta}_\tau} (y_i - X_i\hat{\beta}_\tau) \right\rangle \quad (4.4)$$

4.3.3 General model specification

In the previous literature, we acknowledge the role of Gold-Platinum in terms of predicting excessive Bitcoin return. Therefore, we refer to the predictability model of Huang and Kilic (2019) as follows:

$$12h \sum_{i=1}^h \log R_{t+i} - \log R_{t+i}^f = \beta_0 + \beta_1 \log GP_t + \varepsilon_{t+h} \quad (4.5)$$

where the left-hand variable denotes excess log return of Bitcoin in regard to the 3-month US Treasury bill, representing risk-free rate as $\log R_t^f$, annualized by the horizon h , while the right hand predictor is logGP. In addition, β_0 is the constant coefficient, β_1 is coefficient of log GP, and ε_{t+h} is the error terms. To follow the convention regarding the natural logarithm in stock return predictability in (Hodrick, 1992), $\log R_{t+1} \equiv \log(R_{t+1}/R_t)$ with P_t is the end-of-month Bitcoin price. In addition, the log GP ratio is measured as the natural logarithm of the ratio of gold to platinum prices.

⁸Therefore, if $n = 2$, we obtain the standard wavelet correlation and cross-correlation, which coincides when solving.

4.3.4 Forecast Error Variance Decompositions from VAR

This methodology will provide us insights that how this volatility of ratio (GP) is transmitted to the Excessive Bitcoin Return. Huang and Kilic (2019) argued that GP is considered as a proxy for an aggregate source of risk in the economy, which could predict stock return and have an association with tail risk. By using this method we can examine how large the ratio of Gold and Platinum is linked to the volatility of Excessive Bitcoin return. Forecast Error Variance Decompositions from Vector Auto Regression was devised by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012). In this paper, we will summarize the basic step to estimate the spillover effects in volatility between two variables.

Initially, we have N-dimensional vector RV_t for the realized variance, which is obtained from a covariance stationary of N-variable through the VAR(p) process:

$$RV_t = \sum_{l=1}^p \Phi_l RV_{t-l} + \epsilon_t \quad (4.6)$$

RV_{t-l} denotes the vector having of realized variance of parameters matrices from the relationship between the Bitcoin Excessive Return and Gold Platinum. $\epsilon_t \sim N(0; \Sigma_\epsilon)$ means that the residual follows i.i.d vector. Φ_l stands for p matrices of the coefficients. Following that, the invertible VAR process are carried out to capture the moving average representation.

$$RV_t = \sum_{l=0}^{\infty} \Psi_l \epsilon_{t-l} \quad (4.7)$$

Ψ_l has $(n \times n)$ matrices which are obtained from the recursion $\Psi_l = \sum_{j=1}^p \Phi_j \Psi_{l-j}$ where $\Psi_l = I_N$ and $\Psi_l = 0$ for $l < 0$. This procedure isolates the forecast errors for further computation, which is improved in the previous literature of Diebold and Yilmaz (2009). Afterwards, Diebold and Yilmaz (2012) introduce their method of constructing H-step-ahead, which means that generalized forecast error variance decomposition will appear in the matrix (The computational equation was represented in Equation 4.7). However, in this work, we referred to Baruník, Kočenda, and Vácha (2016) study, which overcomes the previous limitations. Specifically, we can deal with the invariant to the variable ordering and measure the level of spillover in directional volatility spillovers.

$$\phi_{ij}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon e_k)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon \Psi_h' e_k)} \quad j, k = 1, \dots, N \quad (4.8)$$

Ψ_h is the vector having the moving average coefficient calculated from the forecast at time t whereas Σ_ϵ stands for the variance matrix for the error vector. k is the k^{th} diagonal element of Σ_ϵ . In addition, e_j and e_k are selection vectors, with one as the j^{th} or k^{th} element and zero otherwise. Especially, the normalization process of each row is

calculated as $\tilde{\theta}_{jk}^H = \frac{\theta_{jk}^H}{\sum_{k=1}^N \theta_{jk}^H}$. Thus, the total interconnectedness from volatility shocks in the estimation to total forecast error variance:

$$S^H = 100 \times \frac{1}{N} \sum_{j,k=1;j \neq k}^N \tilde{\theta}_{jk}^H \quad (4.9)$$

It is worth noting that $\sum_{k=1}^N \tilde{\theta}_{jk}^H = 1$ and $\sum_{j,k=1}^N \tilde{\theta}_{jk}^H = N$. In this paper, we replicated the 12-month rolling window as one year from $(t - 11)$ to point t . In addition, we choose the VAR lag length based on AIC criteria.

4.4 Results

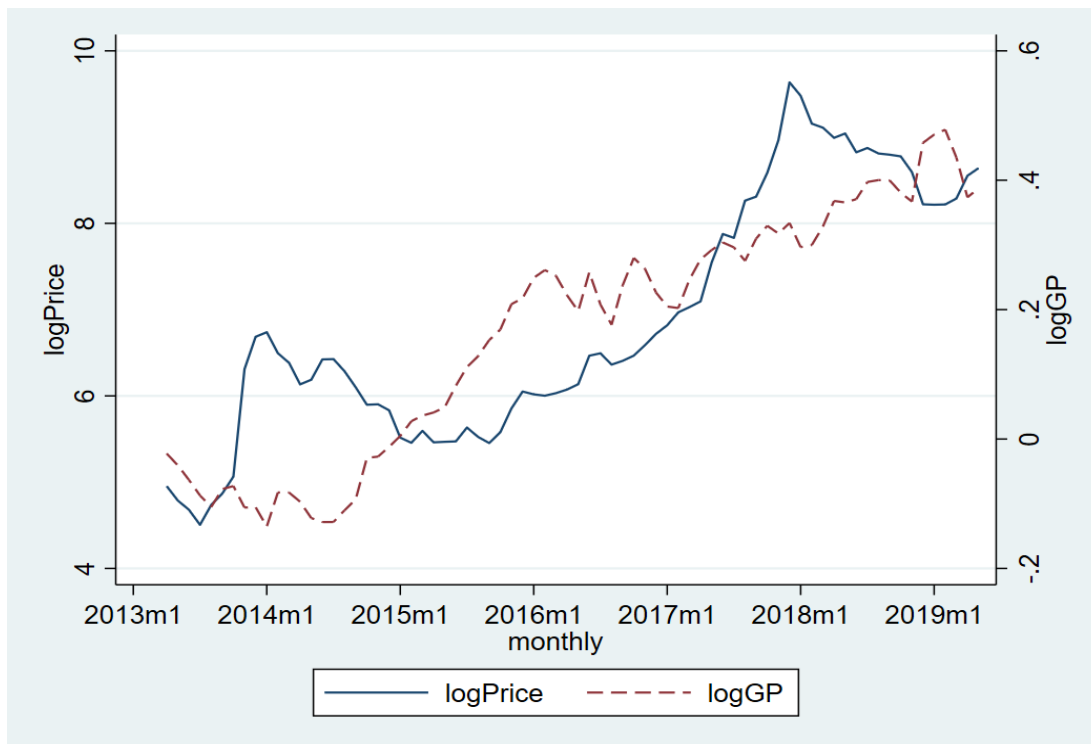
4.4.1 Data description

Our data are retrieved from two main sources: (i) coinmarketcap.com for daily Bitcoin price from 1st May 2013 to 28th October 2019 and (ii) Thomson Reuters for Gold and Platinum prices. We calculated the natural logarithm daily return based on Bitcoin prices. Afterwards, we constructed the average monthly return⁹ for Bitcoin from the average daily return instead of using the beginning and ending data, which implies the forgettable memories in this period. Our main reason is used for monthly data because we consider Bitcoin as the alternative investment (not speculative asset with daily trading data). In addition, the conventional investment model prefers using monthly data to daily data due to the avoidance of noise trading and the unrealistic of investing strategies in restructuring portfolio by each month (Huang and Kilic, 2019; Yang, Zhang, and Zhang, 2020). In the Bitcoin studies, the use of monthly data could be referred to Dwyer (2015), Eom et al. (2019), and Chevapatrakul and Mascia (2019) for the realized volatility and returns. More importantly, we employed two types of robustness check to examine whether log GP is a persistent factor in investing strategies (monthly data) and speculative strategies (daily data) or not. In addition, the test of the January effect, which significantly increases the gold consumption in the world, will be examined. Because the controversial debate regarding data sources in cryptocurrency research is mentioned in Alexander and Dakos (2020), we also used alternative sources of Bitcoin prices from Thomson Reuters, which was collected from *Bitstamp* for robustness check our validity of data sources.

Figure 4.1 plots logGP ratio and Bitcoin prices. We observe that the average monthly Bitcoin price goes up during the period from 2013 to 2019. Noticeably, after the crash of Bitcoin in January 2018, Bitcoin prices went down but the GP ratio increased. It is very interesting to conclude this characteristic of these two assets (counter-cyclical and interconnected relationship in crisis period), which is an element to predict the asset pricing model of (Huang and Kilic, 2019). Table 4.1 shows descriptive statistics

⁹The average monthly is calculated as $\bar{R} = 1n \sum_{i=2}^n \ln(P_i P_{i-1})$. We refer to the calculation from the study of Huynh, Wang, and Vo (2021) for monthly average Bitcoin returns.

of our variables. Similar to the equity valuation ratio of Huang and Kilic (2019), the correlation between EBR and logGP is high (ρ Pearson = -0.5501 and p-value < 0.01). Our AR(1) coefficient for log GP is 0.99, which means inside the unit circle.



Notes: This figure shows the natural logarithm of the Gold-Platinum prices Ratio and Bitcoin prices from 2013 to 2019. Our data is monthly frequency.

FIGURE 4.1: LogGP ratio and Log Bitcoin price

The excessive Bitcoin return over the risk-free rate is negative. It means that the investment in Bitcoin does not earn the positive return in comparison with the 3-month US Treasury bill. Although the average excess return is negative, the variable is positively skewed and fat-tailed. This implies that investors gain large Bitcoin return during the period from May 2013 to October 2019; however, it is also reasonable to conclude that investors suffer due to unexpected losses. The EBR rejects the null hypothesis of normality of the distribution at the 1% significance level. Thus, the variable does not follow a normal distribution. On the other hand, log GP tends to have normal distributions with the Jarque-Bera test rejected at the 10% significance level.

In order to avoid spurious results of our estimates, we need to perform stationary tests. Formally, we performed different tests of stationary to assure that our variables are stationary. The results are presented in Table 4.2.

We find that the EBR is stationary at any level while logGP is only stationary with a weak condition when controlling for trend effects using the Augmented Dickey Fuller (ADF) and Phillip-Perron (PP) test, respectively. Therefore, the results suggest to

TABLE 4.1: Descriptive statistics of Gold-Platinum and excessive Bitcoin return

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB
EBR	-0.0060	0.0132	-0.0383	0.0564	0.8901	8.1243	95.64***
logGP	0.1918	0.2008	-0.1333	0.5558	-0.1912	1.8441	4.817*

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. JB denotes Jarque-Bera test for normality. Monthly data from May 2013 to October 2019. EBR is Excess Bitcoin Return, calculated by the discrepancy between real Bitcoin return and risk-free rate return of 3-month US Treasury bill. Gold fixing prices are collected from the London Bullion Market Association while platinum fixing prices are retrieved from London Platinum and Palladium Market. These data are daily and recalculated by average daily price to monthly prices. logGP was calculated by the natural logarithm of the ratio between Gold and Platinum prices by monthly frequency.

TABLE 4.2: Stationary test

Variable	ADF (No-trend)	ADF (Trend)	PP	PP (Trend)
EBR	-5.079***	-7.075***	-5.119***	-7.167***
logGP	-0.239	-3.276*	-0.044	-3.236*

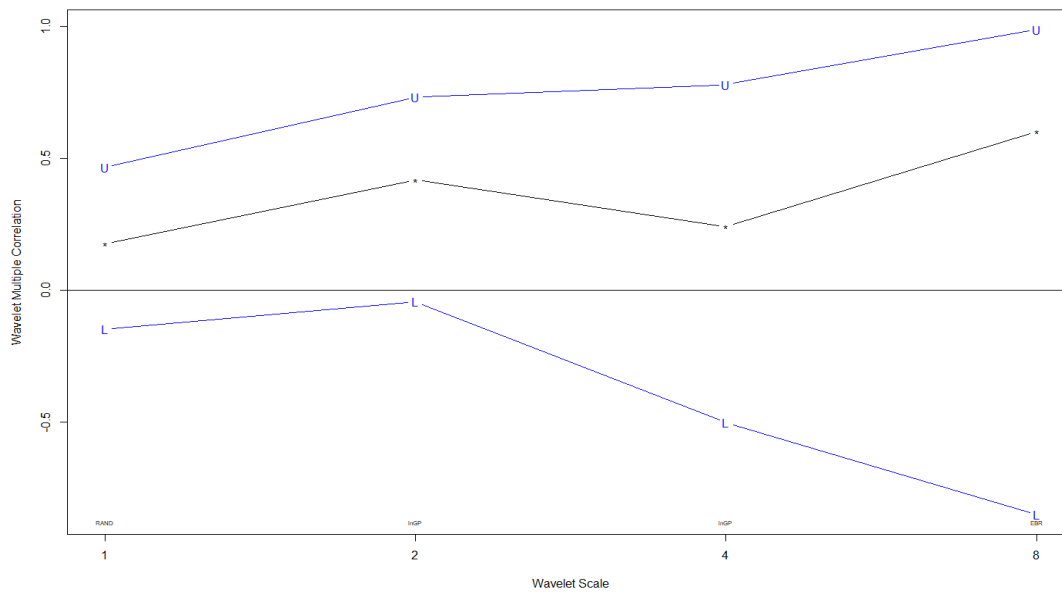
Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. ADF denotes Augmented Dickey-Fuller test, which strictly follows a unit-root process with additional lags of the first-differenced variable while PP stands for Phillip Perron test (1988), using Newey-West standard errors to account for serial correlation.

also put time-effects in the predicted return regression. In addition, when we tested the first-difference of log GP, we found that this variable is stationary (ADF: $p < 0.001$ and PP: $p < 0.001$). Because our data has the weak stationary at the original level $I(0)$ and the strong stationary at the first-difference $I(1)$, which is similar to the previous study of Huang and Kilic (2019). Hence, apart from OLS and VAR in our empirical section, we will examine the co-integration test and use the Vector error-correction models (VECM) to examine the relationship between log GP and Excess Bitcoin Return.

4.4.2 Wavelet Multiple Correlation Results

Before starting with expected return prediction, this part examines correlations between Gold-Platinum and Excessive Bitcoin Return under the changes of cyclical scale. As the previous part mentioned that the interconnectedness of these variables varying with the countercyclical. Therefore, using the wavelet multiple correlation, devised by Fernández-Macho (2012) to bring better statistical interpretation due to the participant of random variables, representing random changes in return. Figure 4.2 shows the wavelet multiple correlation of triple variables (Gold-Platinum ratio, Excessive Bitcoin Return, and Normal random distribution variables) with the chosen of the maximal overlap discrete wavelet transform (MODWT) as length of 8 (Liow et al., 2019; Reboledo and Rivera-Castro, 2014).

Our result indicates that the multiple correlation lies in average level. However, this correlation value starts at nearly a half of 0.5 and rises at the increasing time scale. In



This graph demonstrates the wave multiple correlation for GP Ratio and Excessive Bitcoin Return. The U-line and L-line correspond to the upper and lower bounds of the 95% confidence interval.

FIGURE 4.2: Wavelet multiple correlation for GP Ratio and Excessive Bitcoin Return

addition, the cross-correlation among log GP, Excess Bitcoin return and randomness appears significance at time-scale 2. In contrast, the time-scale 4 and 8 tend to be insignificant. It means that the relationship between Gold-Platinum Ratio and Excess Bitcoin Return ruled out by longer time-horizon. Saying in another way, each two time-scale, the movement of the ratio of Gold and Platinum and Excess Bitcoin Return is likely to have the same movement (going up or going down). As seen in the first scale (random changes), this correlation is lower than having Gold-Platinum existence in terms of correlated comparison. Then, under longer time horizons, the dependence of Gold-Platinum Ratio on Excessive Bitcoin Return is decreasing while itself correlation, EBR, increases. This means that Excessive Bitcoin return could be relied on random changes, itself and GP at different time horizons.

The Wave multiple correlation result reveals the existence of randomness between Bitcoin return and logGP for the periods of time longer than one month. This method consists of a set of multi-scale correlations, calculated by the square root of the regression coefficient from the linear model of wavelet coefficients so that this coefficient of determination has the maximum value. By doing so, we can see the dependence between two continuous variables with the existence of randomness over the different timescales. Although this method is applied in financial and cryptocurrency world as well as the precious metals world (Omane-Adjepong, Ababio, and Alagidede, 2019; Omame-Adjepong and Alagidede, 2019; Hkiri et al., 2018; Boubaker and Raza, 2017; Das et al., 2018; Tweneboah and Alagidede, 2018), to the best of our knowledge, this paper is the first application between the ratio of gold and platinum to examine the

dependence with Bitcoin return under randomness. Apart from the statistical evidence that Gold and Platinum have a dependence on Bitcoin by two different time-scale, this paper focuses on the predictability of these precious metals on ‘Digital Gold’, mentioned in the following parts.

4.4.3 Bitcoin return predictability

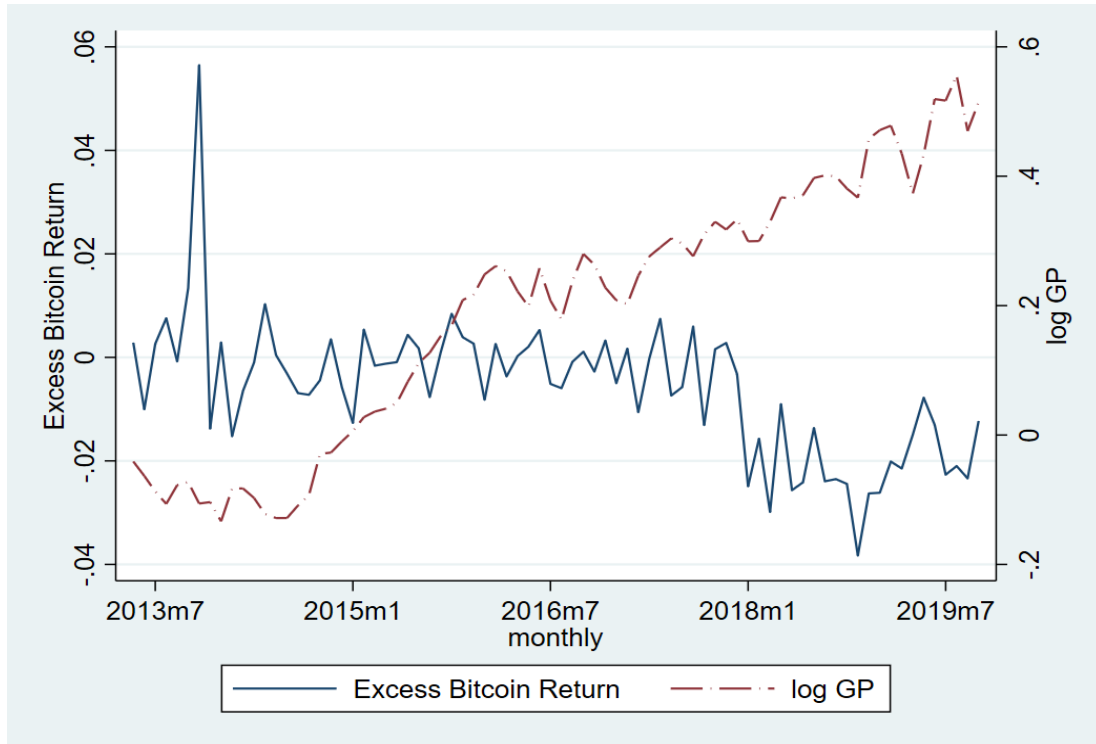
There are two main reasons for us to implement OLS, VAR, and quantile regression as Bitcoin return predictability instead of quantile autoregression. First, the conventional of asset pricing model usually considers the exogenous factors than itself in terms of explaining asset returns (Huang and Kilic, 2019; Fama and French, 2015; Hodrick, 1992). Second, Quantile autoregression (including the lagged terms of the dependent variable) has possible misspecification (refer to the comment part of studies of Koenker and Xiao (2006)). Therefore, we implemented two methods to examine the role of Gold-Platinum in terms of Bitcoin return predictability (OLS, VAR, and quantile regression, for robustness), which only focus on exogenous determinants. Table 4.3 shows the results of Bitcoin return predictability with different long-horizon time by using OLS.

TABLE 4.3: Bitcoin return predictability by Ordinary Least Squares

Bitcoin excess return	1 month	3 months	6 months	1 year
$\log GP_{(t)}$	0.0481**	0.0539***	0.0541*	0.0345**
R^2 adjusted (%)	40.21	43.26	41.25	48.84
Time-effect control	Yes	Yes	Yes	Yes

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Bitcoin returns are calculated from overlapping monthly data and the robust OLS regressions are applied. The further estimations based on Newey and Kenneth (1987) with correcting the heteroskedasticity, autocorrelation consistent (HAC) and robust standard errors are consistent to our results. Long-horizon returns are constructed from overlapping monthly returns. Figure 4.3 demonstrates the relationship between the ratio of Gold-Platinum prices and Excess Bitcoin Return.

As seen in Table 4.3, the Gold-Platinum ratio is a very good predictor to forecast the Bitcoin return. All coefficients are positive and significant. This means that when Gold prices increase relatively to an increase of Platinum prices, the expected Bitcoin return also increases. It means that the logGP high when the Bitcoin prices are low; therefore, the Bitcoin risk premium is high, giving the ratio of GP the predictive power to the Bitcoin future return. Thus, if investing into this market, investors need to require the higher premium to subsidy for the risk they might bear in the future. Our findings are in-line with the previous literature (Huang and Kilic, 2019). The predictability of the model varies from 40.21% to 48.84%. In addition, our estimated co-efficient on logGP for one-month horizon is 0.0481 and the standard deviation of logGP is 0.2008. It implies that one standard deviation increase in logGP has in association with 0.96% increase in Bitcoin excess return in the following month. We can easily interpret the remainder of significant coefficients in our estimated models for the changes in logGP,



This figure shows the natural logarithm of the Gold-Platinum prices Ratio and Excess Bitcoin Return from 2013 to 2019. Our data is monthly frequency.

FIGURE 4.3: LogGP ratio and Excess Bitcoin Return

which associates with the positive increase in the Bitcoin excess return. To avoid the spurious results raised from weak stationary time-series, we also employed the Vector error-correction models (VECM) for Excess Bitcoin Return and log GP with at least one cointegrating equations (Johansen tests for cointegration). Our results are still robust. In addition, we also extracted the residual from our regression to test whether the residual is stationary at $I(0)$ or not. Consequently, all of our residual from regression are $I(0)$ ¹⁰.

Table 4.4 demonstrates the predictability of the ratio of Gold-Platinum on the Excessive Bitcoin Return (EBR) by using Vector Auto Regressive model (VAR). The previous literature of Hodrick (1992) uses Vector Autoregression (VAR) framework to predict the overlapping returns. As the same pattern to the OLS estimation, the ratio of gold and platinum is still a good predictor of the Excessive Bitcoin Return from all horizons from one month to one year.

In this part, our results indicate that the ratio of logGP is predictive tool to forecast the Excessive Bitcoin return in the upcoming months (with our estimated windows as 1, 3, 6 and 12 months). We find that the ratio (log GP) provides explanatory significance

¹⁰T-statistics values of our residual estimates for each horizon (1 month, 3 months, 6 months and 12 months) are -7.85, -7.79, -8.83 and -5.48, respectively.

TABLE 4.4: Bitcoin return predictability by Vector Auto Regressive (VAR)

Bitcoin excess return	1 month	3 months	6 months	1 year
$\log GP_{(t)}$	0.0419*	0.0516**	0.0458**	0.035*
R^2 adjusted (%)	41.59	43.44	43.42	48.85
Time-effect control	Yes	Yes	Yes	Yes

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. VAR method is employed as the study of Hodrick (1992) for financial asset predictability, which imposes parametric assumption. Long-horizon returns are constructed from overlapping monthly returns. Figure 4.3 demonstrates the relationship between the ratio of Gold-Platinum prices and Excess Bitcoin Return.

around 40% change in the Bitcoin excess return. In addition, all coefficients are significantly positive, which implies the persistent and strong association with future Bitcoin return while the ratio of Gold-Platinum was considered as the proxy for the potential aggregate source of risk in the economy in the near future. In addition, when using the VAR Granger to examine the causal relationship between this ratio and the Excessive Bitcoin return, we found that the changes in Gold/Platinum ratio cause the changes in Bitcoin return with Granger causality Wald tests ($\chi^2 = 5.104$, $p < 0.05$). However, we do not find the further evidence in the opposite direction (Bitcoin \nrightarrow Gold/Platinum ratio, $\chi^2 = 0.0003$, $p = 0.98$). It implies that there is not only predictability of Bitcoin return, this ratio also causes the changes. Clearly, the Bitcoin return is driven by the behavior in trading the precious metals.

As mentioned in the literature, the ratio of natural logarithm between Gold and Platinum prices has the systematic risk information. Therefore, we examine how this ratio correlates with the Economic Policy Uncertainty from Baker, Bloom, and Davis (2016). We find that $\log GP$ has strong correlation ($\rho = 0.7823$, $p < 0.01$); $\beta_{EPU} = 0.00029$ with explanatory R^2 as 94% to $\log GP$ ratio. Therefore, we confirmed that the increase in $\log GP$ at time t conveys the variation in aggregation market risk, which would increase the expected Bitcoin return in the future as the risk premium or discount rates for the alternative investment.

TABLE 4.5: Volatility spillover table rows (to), columns (from)

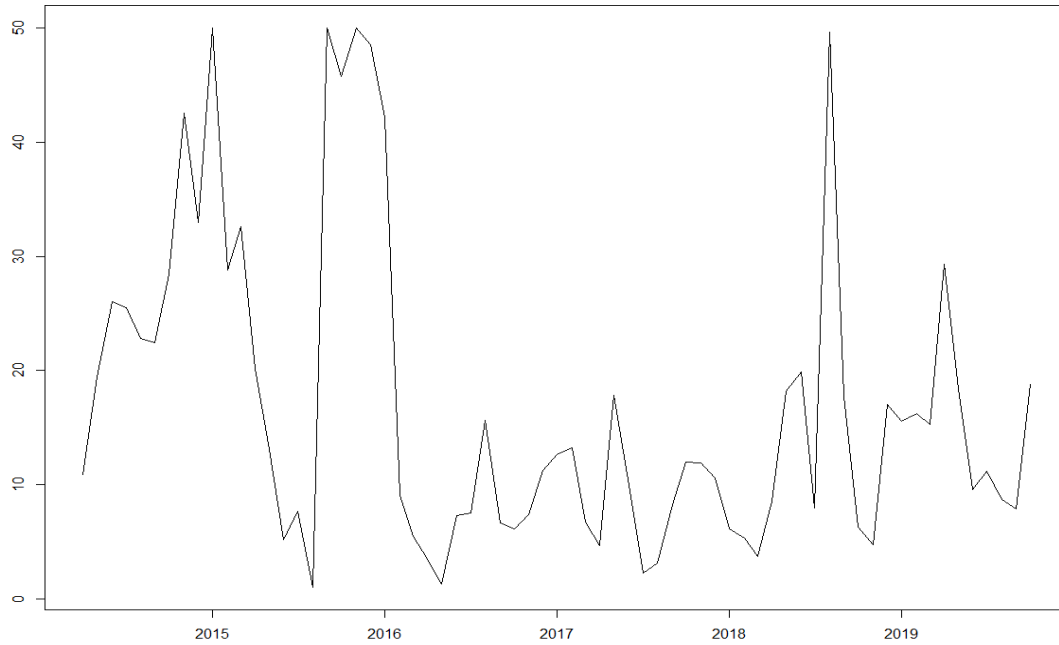
	One to four days		Five to inf days	
	EBR	lnGP	EBR	lnGP
\rightarrow EBR	36.71	0.78	40.11	22.4
\rightarrow lnGP	0.11	0.53	11.16	88.2

Notes: Table 4.5 decomposes the volatility spillover indices from one variable to another variable. The net spillover effects between net-contributors and net-recipients of volatility spillovers across two markets are 2.34% and 20.74% for the short-term and long-term periods, respectively.

Table 4.5 represents that the contribution of lnGP to the Excessive Bitcoin return in

short term is only 0.78% while this effect is stronger in the long run, up to 22.4%. It means that the changes in the volatility of Bitcoin are not associated with the contemporaneous shocks but there exists the dynamic and time-varying link. Although the study of Dyrberg (2016a) confirms that Gold and Bitcoin share similarities in hedging capabilities and the symmetrical reaction, our results support the findings from Baur, Dimpfl, and Kuck (2018) that Bitcoin has exhibits distinctively different volatility and return features compared to gold. If Bitcoin and gold share the similar characteristics as Dyrberg (2016a) suggestion, their volatility transmission through frequency connectedness should be low. From another perspective, we do find that the ratio of natural logarithm in Gold and Platinum prices have the higher volatility connectedness. Thus, this study also contributes to the existing literature by examining the spillover effects between two kinds of assets. In addition, the role of ‘flight-to-quality’ of gold has been confirmed by many previous studies (see from Erb and Harvey (2013) and Barro and Misra (2016)), the volatility spillover could be a potential channel for the further explanation of an increase in the expected return of Bitcoin. As seen in Figure 4.4, on average, the time-varying spillover index exhibits a great degree of fluctuation around the volatility spillover indices, ranging from about 10% to 50%. Especially, in the period of Bitcoin crash, the link of volatility between Bitcoin and this ratio is quite low while the booming period is witnessed the stronger volatility contagion. Our results imply that shocks from Gold and Platinum markets do not necessarily and substantially impact the volatility of Bitcoin market over the whole sample period, but the degree of volatility spillover varies over time. In addition, it also confirms the predictability power of this ratio to the Bitcoin return, which might be misunderstood by the high dependence volatility resulting in the return. Hence, we can confirm the gold and platinum prices can largely be explained by the same risk factors causing the cryptocurrency market.

Our findings manifest positive coefficients of log GP in terms of predicting the expected Bitcoin return. Using the economic intuition from (Huang and Kilic, 2019; Bouri, Wohar, et al., 2019; Wolff and Neugebauer, 2019; Gao, 2016), we attempt to explain the expected premium in investing in Bitcoin. The increase in log GP at time t implies that the ratio of log GP_t is relatively higher than log GP_{t-1} . Meanwhile, log GP is insulated from shocks to consumption. More importantly, gold prices fall by less than platinum prices in these shocks because gold has two functions, namely consumption and storage (as many financial institutions are using as collateral). In contrast, Platinum has main purpose of jewelry. Thus, the increase of log GP reflects the rising storage behaviors from systematic risk. This factor significantly increases the expected Bitcoin returns in time $(t + 1)$, which means that expected price $E(P_{t+1})$ should be relatively higher than the current price P_{t+1} . It implies the higher required risk premium for investors to invest in Bitcoin.



Notes: We also plot the total volatility Spillover index using a 365-day rolling window estimation, equivalent 12 months because Bitcoin does not have trading gap time as well as non-working days.

FIGURE 4.4: Spillovers from volatility by using 12-month window rolling

4.4.4 Robustness check

The quantile regression results for robustness in Table 4.6 suggests that the ratio of GP would be good at predicting Bitcoin return if investors choose to hold less than one-year maturity. Precisely, the GP predictor is well sensible to predict the Bitcoin return in the short-term period.

Interestingly, the one-year excessive return does not experience any statistical coefficients, which implies that the ratio of Gold-Platinum is the weakly predictive tool for the long horizon investment (equally and above one-year). In addition, the R-square indicator also shows that one-month (with the highest values) is likely to be an appropriate time that this ratio plays its predictive role in Bitcoin excessive return. The use of quantile regression in asset pricing is employed by several papers (Pedersen, 2015; Huynh, Nguyen, and Duong, 2018). Apart from the OLS with Newey and Kenneth (1987) correction and Vector Auto Regression with matrix construction, this paper also confirms the robustness of Gold-Platinum ratio in terms of forecasting the Bitcoin excessive return.

Table 4.7 also confirms that the effect of new year does not influence the predictability of this ratio (Gold-Platinum). Although the previous studies indicate that gold prices might increase in New Year due to several reasons, Gold-Platinum remains its characteristic to predict Bitcoin excessive return in the following month. Finally, we confirm the characteristic of Gold-Platinum to predict the future Bitcoin return through our model during the period from 2013 to 2019.

TABLE 4.6: Bitcoin return predictability by quantile regression

Bitcoin excess return	1 month	3 months	6 months	1 year
Quantile (q=10)				
$\log GP_{(t)}$	0.7594***	0.4651**	0.5215***	-0.1864
R^2 adjusted (%)	83.91	76.71	79.76	76.74
Quantile (q=25)				
$\log GP_{(t)}$	0.8077***	0.3695*	0.5151***	-0.1819
R^2 adjusted (%)	86.85	80.01	80.39	75.79
Quantile (q=50)				
$\log GP_{(t)}$	0.8056***	0.3101***	0.2369***	-0.2259
R^2 adjusted (%)	85.88	79.42	77.54	72.05
Quantile (q=75)				
$\log GP_{(t)}$	0.8028***	0.5284***	0.5084***	-0.1307
R^2 adjusted (%)	84.57	76.99	74.74	69.23
Quantile (q=90)				
$\log GP_{(t)}$	0.7193***	0.6851***	0.6490***	-0.3593*
R^2 adjusted (%)	83.59	77.9	71.7	68.43
Time-effect control	Yes	Yes	Yes	Yes

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Bitcoin returns are calculated from overlapping monthly data and the robust OLS regressions are applied. Long-horizon returns are constructed from overlapping monthly returns.

TABLE 4.7: Bitcoin return predictability with January effect sub-sample

Bitcoin excess return	With January effect	Without January effect
$\log GP_{(t)}$	0.0868*	0.0434*
R^2 adjusted (%)	43.36	41.83
Time-effect control	Yes	Yes
Robust effect	Yes	Yes

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The further estimations based on Newey and Kenneth (1987) with correcting the heteroskedasticity, autocorrelation consistent (HAC) and robust standard errors are consistent to our results.

Another robust check in our paper is a change in the frequency of data. We constructed the daily data for examined whether the predictive power of log GP still holds or not. Table 4.8 demonstrates the daily characteristics of Excess Bitcoin Return and log GP. There are two main worth noting things from this table. First, our variables have non-normal distribution. Second, the stationary feature is satisfied with the trend existence. It also implies that we should consider the time-effect as well as the Vector-Error-Corrected Model for our robust check.

TABLE 4.8: Descriptive statistics for daily data

Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF	ADF (trend)
Daily EBR	-0.8191	0.8563	-0.6057	1.7915	216.7***	-2.209	-3.697**
Daily Log GP	0.0888	0.0887	-0.2290	1.8430	114.6***	-0.162	-3.853**

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. JB denotes Jarque-Bera test for normality. ADF stands for Dickey-Fuller stationary test with- and without- trend. Daily data from 1st May 2013 to 31st October 2019. EBR is Excess Bitcoin Return, calculated by the discrepancy between real Bitcoin return and risk-free rate return of 3-month US Treasury bill. Gold fixing prices are collected from the London Bullion Market Association while platinum fixing prices are retrieved from London Platinum and Palladium Market. These data are daily. logGP was calculated by the natural logarithm of the ratio between Gold and Platinum prices by daily frequency.

Table 4.9 demonstrates the predictability of log GP on Bitcoin daily return with time-horizon from 1 day to 7 days from another data source (Bitstamp). Our robust results are also in line with the previous findings that when the ratio of Gold and Platinum increases, the expected Bitcoin return also rises. Therefore, our main results are robust when the frequency of our data ranges from daily to one year. In addition, the study of Alexander and Dakos (2020) raised a concern that cryptocurrency market index varies significantly, depending on the data source and the index selected. Therefore, we employed another source suggested by Alexander and Dakos (2020) and Corbet et al. (2018) to consider whether our results are robust or not. Overall, log GP still holds its predictive power on the Bitcoin excess return.

TABLE 4.9: Bitcoin predictability by Ordinary Least Squares with data from Bitstamp

Bitcoin excess return	Daily (Bitstamp)		Monthly (Bitstamp)			
	1 day	7 day	1 month	3 month	6 month	12 month
$\log GP_{(t)}$	4.1326***	4.2376***	0.0552*	0.0694***	0.071	0.0439**
R^2	34.98	34.84	26.1	30.46	28.24	33.79
Time-effect control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$; * $p < 0.1$. Bitcoin returns are calculated from overlapping daily data and the robust OLS regressions are applied. The further estimations based on Newey and Kenneth (1987) with correcting the heteroskedasticity, autocorrelation consistent (HAC) and robust standard errors are consistent to our results.

To examine whether the predictive power of the ratio log GP holds or not, we substituted Bitcoin data with data for Ethereum. Again, we find an association between the Excessive Ethereum returns and the natural logarithm of Gold and Platinum prices.

The results are available in Appendix C.1, C.1, and D.3. Therefore, the validity of this ratio does not only apply to Bitcoin but also other alternative coins (altcoin) in the cryptocurrency market.

4.5 Conclusion

In this study, we examined the prediction power of Gold-Platinum as an economic state variable on Bitcoin. By applying wavelet multiple correlation and several econometrics models, we find that Gold-Platinum is able to predict Bitcoin particularly well in the short-term period (less than one year). When the price of gold relative to platinum increases, Bitcoin return goes up as well. This is consistent to the literature and shows that Bitcoin can be indeed considered a safe haven asset and a *store of value* with similar characteristics as gold. Although Bitcoin has yet to see a major global financial crisis, our findings have important implications for investors who are looking for alternatives for hedging their investments during economic distress, as gold has proven less reliable in recent years. Future research might investigate whether the results are consistent across different cryptocurrencies. Our results are also persistent with robustness check by using different quantile levels and January effects (changes in the gold demand). By using the ratio of Gold-Platinum, we accomplish one of the advantages namely the counter-cyclical form suggested by Huang and Kilic (2019) from the economic background. In our model, Gold-Platinum also reflects the dynamics and predictability of Bitcoin return during the financial turmoil. However, the role of institutional players need to be more examined in both gold and Bitcoin markets. This is still a promising avenue for the future researches.

Chapter 5

Does Bitcoin React to Trump's Tweets?[§]

5.1 Introduction

President Donald J. Trump's incessant and sometimes caustic tweeting gathers a worldwide audience. Although Twitter might or might not be an official channel for US policy¹, Trump's tweets are political news and escalate global uncertainty as suggested by the nearly fourfold increase in the Index of Global Economic Policy Uncertainty from 230.75 at the start of Trump's presidency in 2017 to 907.43 in November 2019.

Financial markets digest Trump's tweets for potential effects, and scholars have documented them. Beckers (2018) found evidence to challenge the Efficient Market Hypotheses after showing that lagged variables for social media news could predict global equity returns the next month. Examining word clusters, Liu (2017) found that Trump tweets featuring 'jobless' and 'worst' preceded equity market declines. Trump tweets also preceded a decline in the S&P500 and an increase in the CBOE Volatility Index during trade disputes with China.

Market values of cryptocurrency now exceed the GDP of 130 countries (Selmi, Tiwari, Hammoudeh, et al., 2018). Cryptocurrency has become a platform for 'Fintech' and 'peer-to-peer' lending. Huynh, Wang, and Vo (2021), Shahzad et al. (2019a), and Wang et al. (2019) have indicated cryptocurrencies could be safe-haven investments, implying the property characteristics (Yuneline, 2019). As investors and researchers ask, 'What drives Bitcoin returns?', studies answer with reference to supply and demand (Ciaian, Rajcaniova, and Kancs, 2016), investor attention (Corbet, McHugh, and Meegan, 2014; Urquhart, 2018), speculative bubbles (Cheah and Fry, 2015), or economic policy uncertainty (Demir et al., 2018). Studies also confirm that social media influences cryptocurrency markets. Urquhart (2016) and Urquhart (2018) found that Bitcoin prices could be predicted and joined Beckers (2018) in contributing an empirical evidence

[§]This chapter is based on Huynh, T. L. D. (2021). Does Bitcoin React to Trump's Tweets?. *Journal of Behavioral and Experimental Finance*, 31, 100546, <https://doi.org/10.1016/j.jbef.2021.100546>. In addition, this work was presented at the online seminar participants at the Brazil Finance Webinar Series, Finance Research Forum (organized by the Department of Finance at Monash University's Malaysia Campus), and the Korean Academic Association of Business Administration (KAABA) Joint International Conference (organized by the Korean Academic Association of Business Administration)

¹<https://edition.cnn.com/2017/06/06/politics/trump-tweets-official-statements/index.html>

disputing the Efficient Market Hypothesis. Shen, Urquhart, and Wang (2019) used a number of hashtags in Twitter platforms and found that the number of tweets written by investors could forecast Bitcoin volatility, volume, or returns.

This study investigates whether Trump's tweets have influenced Bitcoin markets. It differs from earlier studies in that we do not define whether those tweets constitute policy announcements or reflect investor sentiment. We presume, instead, that they obviously constitute a statement from the US Chief Executive, and that—as aforementioned studies proved—they can impose uncertainties on Bitcoin markets. More specifically, we textually assess the sentiment of 13,918 Trump tweets covering January 2017 to January 2020. We cluster text into negative words (indicating downbeat or disapproving attitudes), positive words (indicating optimistic or approving attitudes), and total words (frequency with which Trump tweets). We then measure their spillover effects on prices and volatility in Bitcoin markets.

This study makes five contributions to scholarly literature during 'The Age of Twitter' (Ott, 2017). First, it adds to studies of relations between perspectives in social media and Bitcoin, an innovative payment network and a new kind of money. Second, it combines state-of-the-art textual analysis and sophisticated Vector Autoregression to assess effects on a financial market. Third, it proposes a factor for predicting Bitcoin returns. Our findings are twofold. First, lagged terms denoting Trump's sentiment significantly predict positive Bitcoin returns, negative trading volume, and mixed volatility, but negative sentiment has a Granger-causal relationship only with volatility. Second, spillover effects of Trump's tweeted sentiments on Bitcoin exhibit time-varying dependence, with longer periods showing greater spillovers since 2019. Additionally, the volatility transmission exhibits large fluctuations during shorter periods. Additionally, our study also contributes to the ongoing studies about financial markets and COVID-19 that Trump sentiment, particularly in the disease outbreak, could act as the predictive tool to the Bitcoin markets. To be more precise, there is a relationship between attitudes towards COVID-19 and the Bitcoin returns as well as volume. However, volatility seems to be immune to changes in the President's sentiment. Finally, US President Donald Trump's tweets can possibly act as the predictive power on Bitcoin's jumps by using the framework of Barndorff-Nielsen and Shephard (2006). Differing from Ahn and Kim (2019) regarding the driving factor of Sentiment disagreement, our study considers specific messages containing valuable information from Donald Trump, known as the US President. Therefore, his opinion has been perceived as a political risk (Burggraf, Fendel, and Huynh, 2019). By doing this, our study offers a channel on how social media influencers could impact the Bitcoin market while the current literature examines the role of peer opinions driving this cryptocurrency market (Ahn and Kim, 2019; Shen, Urquhart, and Wang, 2019; Urquhart, 2018).

The paper proceeds as follows. Section 5.2 generalizes the theoretical framework to

investigate how Trump's sentiment might impact cryptocurrency markets. Section 5.3 discusses our method. Section 4.3 summarizes how we collect, process, and characterize data. Section 5.5 presents findings regarding our research question. Section 5.6 concludes.

5.2 Theoretical framework

We build upon the theoretical frameworks of Schwert (1981) and Wagner, Zeckhauser, and Ziegler (2018) concerning how prices of financial assets respond to the political news. Since Trump's tweets could be considered as news (Ajjoub, Walker, and Zhao, 2020; Burggraf, Fendel, and Huynh, 2019), this study extends an understanding of Bitcoin reactions to the news released from the White House. Simply put, if markets reflect the optimal news from political outcomes, there are changes in differences between expected discounted payoff between two possible states and the ex-ante probability that this outcome happens.

P_i is the cryptocurrency price (i) prior to the date Trump posts a tweet. $P_{i,N}$ and $P_{i,P}$ denote the expected prices of cryptocurrency given Trump's expression of negative and positive sentiments. In addition, π_N and $1 - \pi_N = \pi_P$ are the probabilities of Trump's sentiments. We make two assumptions. First, discounting over a short period is included. Second, risk aversion is a minor consideration.

$$P_i = \pi_N P_{i,N} + \pi_P P_{i,P} \quad (5.1)$$

The price change for Bitcoin given that Trump has tweeted negative words is given by.

$$\Delta P_i = P_{i,N} - P_i = (P_{i,N} - P_{i,P})(1 - \pi_N) \quad (5.2)$$

In sum, prices change once Trump expresses a positive or negative sentiment. That is, investors who might have had no particular impression form one after Trump tweets. We scale the previous equations by the initial price. Thus, returns once a Trump tweet appears are given by.

$$R_i = \frac{P_{i,N} - P_i}{P_i} = \frac{(P_{i,N} - P_{i,P})(1 - \pi_N)}{P_i} \quad (5.3)$$

Each form of cryptocurrency responds to Trump's sentiment differently depending upon the sign and magnitude of the spread between $P_{i,N}$ and $P_{i,P}$. So, we hold the view of how investors react and expect on the cryptocurrency prices. If the negative and positive tones of Trump diverged significantly over the period, it would explain why cryptocurrency prices responded strongly. Therefore, in the following part, we would

like to mention how we clean up the data and calculate the Trump sentiment for further estimating the expected prices that investors hold in the cryptocurrency market.

5.3 Methodology

5.3.1 Textual analysis

We first counted how many words appeared in a Trump tweet. Then we consulted the 2016 Loughran and McDonald Master Dictionary to determine how many negative and positive sentiments Trump expressed. Although Ahn and Kim (2019) used a different sentiment dictionary to correlate disagreeable sentiments and Bitcoin prices' fluctuations, we adopted Loughran and McDonald, which is synthesized from Loughran and McDonald (2011), Bodnaruk, Loughran, and McDonald (2015), and Loughran and McDonald (2016) because it specifies sentiment words that Tetlock (2007) used in their financial context analyses—for example, *loss(es)*, *impairment*, *adverse(ly)*, etc. We created a proxy for negative words as the ratio of negative to total words in each tweet:

$$\text{Negativity} = \frac{\text{The number of negative words}}{\text{The total words}} \times 100 \quad (5.4)$$

We replicated the procedure to create a proxy for positive words. We also examined the impact of total words in each Trump tweet. The natural logarithm of that total is used for the total of words.

5.3.2 Spillover effects

We examined whether negative and positive words in Trump's tweets spilled over into Bitcoin trading. We followed Diebold and Yilmaz (2009) in measuring the volatility of any spillover. The method employs forecast error variance decompositions from VAR, but it has two disadvantages: it depends on the order of variables, and it measures only total spillovers. We turned to Baruník, Kočenda, and Vácha (2016) and Diebold and Yilmaz (2012), who capture individual effects by considering invariant-to-variable ordering. Their method is widely applied in financial contexts (Baruník and Kocenda, 2019; Baruník and Křehlík, 2018; Yarovaya, Brzeszczyński, and Lau, 2016). Recently, the study of Foglia and Dai (2021a) employed this method to examine how cryptocurrency uncertainty index could impact the cryptocurrency market. Our procedure initially delivered n -dimensional vector RV_t , that has stationary VAR(p) under the following process:

$$RV_t = \sum_{l=1}^p \Phi_l RV_{t-l} + \epsilon_t \quad (5.5)$$

The residual follows the i.i.d vector as $\epsilon_t \sim N(0; \sum_{\epsilon})$ whereas Φ_l denotes p matrices having the coefficients. Following that, the invertible VAR process extracts the moving

average representation.

$$RV_t = \sum_{l=0}^{\infty} \Psi_l \epsilon_{t-l} \quad (5.6)$$

We obtained $(n \times n)$ matrices from the recursion $\Psi_l = \sum_{j=1}^p \Phi_j \Psi_{l-j}$ where $\Psi_l = I_N$ and $\Psi_l = 0$ for $l < 0$. This procedure isolates forecast errors for further computation, which is improved in a previous study by Diebold and Yilmaz (2009). Diebold and Yilmaz (2012) later introduced a method of constructing H-step-ahead point forecasts such that generalized forecast error variance decomposition appears in the matrix:

$$\phi_{ij}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_{\epsilon} e_k)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_{\epsilon} \Psi_h' e_k)} \quad j, k = 1, \dots, N \quad (5.7)$$

This vector has a moving average coefficient calculated from the forecast at time t . Σ_{ϵ} denotes the variance matrix for the error vector. k is the k^{th} diagonal element of Σ_{ϵ} . e_j and e_k are selection vectors, with one as the j^{th} or k^{th} element and zero otherwise. Especially, the normalization process of each row is calculated as $\tilde{\theta}_{jk}^H = \frac{\theta_{jk}^H}{\sum_{k=1}^N \theta_{jk}^H}$. Thus, total interconnectedness from volatility shocks in the estimation of total forecast error variance is given by:

$$S^H = 100 \times \frac{1}{N} \sum_{j,k=1; j \neq k}^N \tilde{\theta}_{jk}^H \quad (5.8)$$

Noted that $\sum_{k=1}^N \tilde{\theta}_{jk}^H = 1$ and $\sum_{j,k=1}^N \tilde{\theta}_{jk}^H = N$. We identified different rolling windows as trading days in one year from $(t - 199)$ to point t because Bitcoin trades continuously. We based VAR lag lengths on Akaike Information Criteria. After calculating total spillover effects, we followed Baruník and Kocenda (2019) to estimate the directional spillover that Trump's sentiments send to Bitcoin and vice versa.

5.4 Data

We collected 13,920 tweets (365,690 words) from *@realDonaldTrump*, each time-stamped in minutes, from January 2017 to January 2020. Trump was inaugurated on January 20th, 2017, so collection starts with the first moments he used his Twitter account in the White House. The majority of Trump's Tweets express consistently negative attitudes about Mexico (Benton and Philips, 2018), US-China trade relations (Burggraf, Fendel, and Huynh, 2019) and the European Financial markets (Klaus and Koser, 2020).

Figure 5.1 shows that negative and positive sentiments moved together from 2017 to 2020. However, the number of negative words slightly exceeds the positive in time-varying connections. There is no significant correlation between proxies for positive and negative sentiments ($\rho = 0.0491$, and OLS regression generating the insignificant

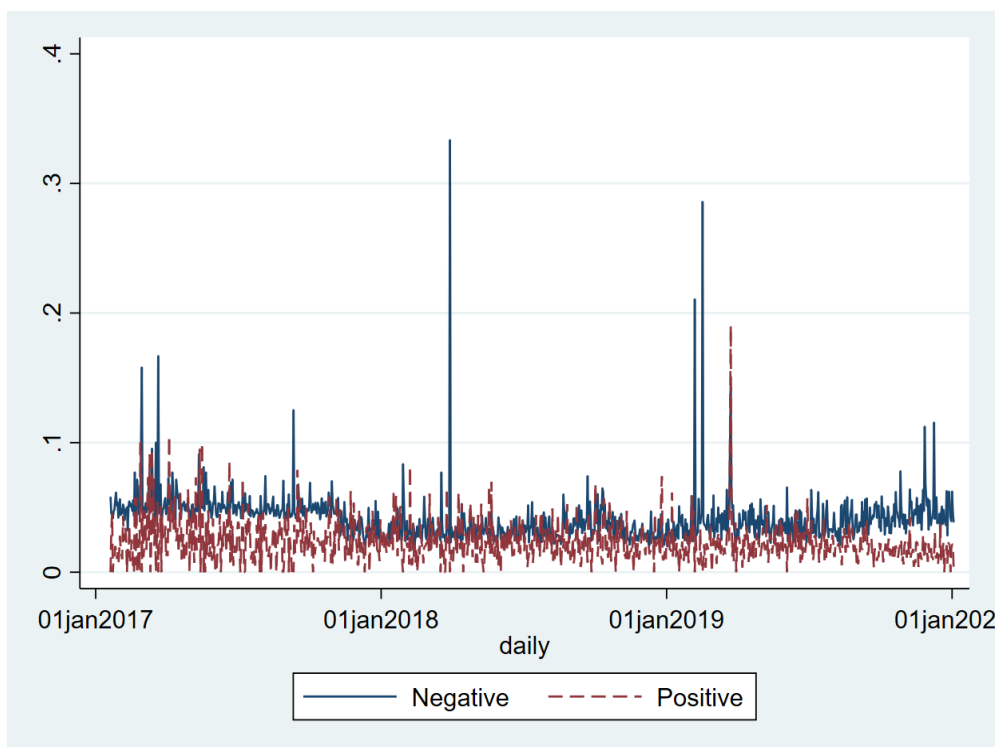


FIGURE 5.1: Time-varying between negative and positive from textual analysis.

coefficient as well, $\beta_{t-stat=0.59} = 0.0214$). Our check implies that Trump's sentiment variables are reliably independent variables.

Bitcoin data are from coinmarketcap.com covering January 2017 to January 2020. We calculated log-returns per Fama and Miller (1972) and the natural logarithm for scaling Bitcoin trading volume. Figure 5.2 indicates a positive correlation ($\rho = 0.2483$ with $p < 0.01$) between the number of negative words and Bitcoin prices from January 2017 to January 2020. The correlation between Bitcoin prices and the proxy for negativity varies with time, so we considered time effects to control this phenomenon.

Bitcoin's average returns during the examined period approximate 0.002 (Table 5.1). Note that negative values from the textual analysis are significantly higher than positive values. Additionally, all variables exhibit non-normal distributions.

TABLE 5.1: Descriptive statistics of Bitcoin and Trump's sentiment

Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB
BTC-Return	0.002	0.042	0.0372	6.5659	567.7***
BTC-Volume	22.261	1.350	-0.9808	3.5838	187***
Negative	0.041	0.019	7.1814	91.989	36000***
Positive	0.023	0.016	2.3721	17.526	1000***
Total	5.514	0.915	-0.6984	3.8341	118.1***

Notes: *** $p < 0.01$, ** $p < 0.05$; * $p < 0.01$. JB denotes Jarque-Bera test for normality.

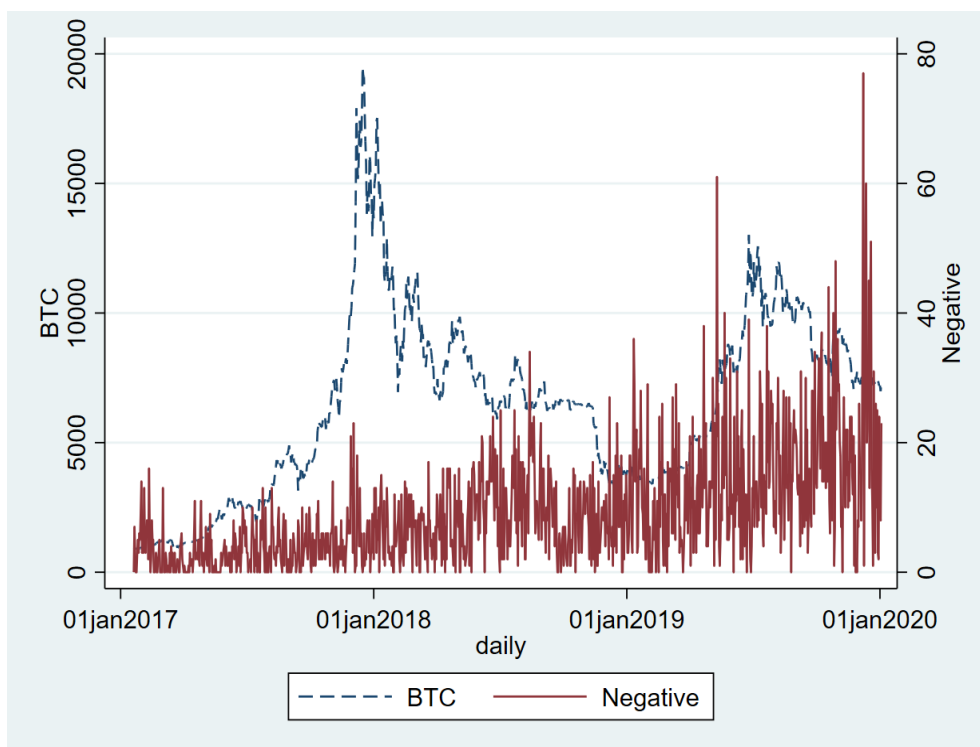
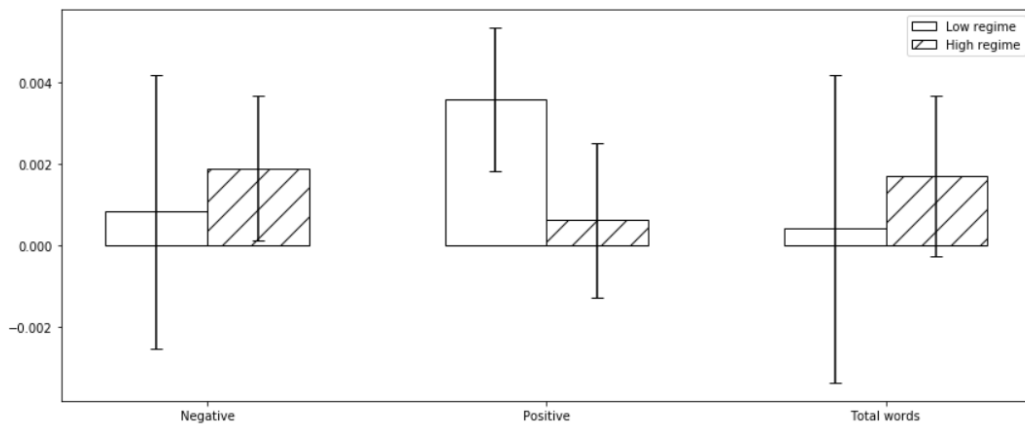


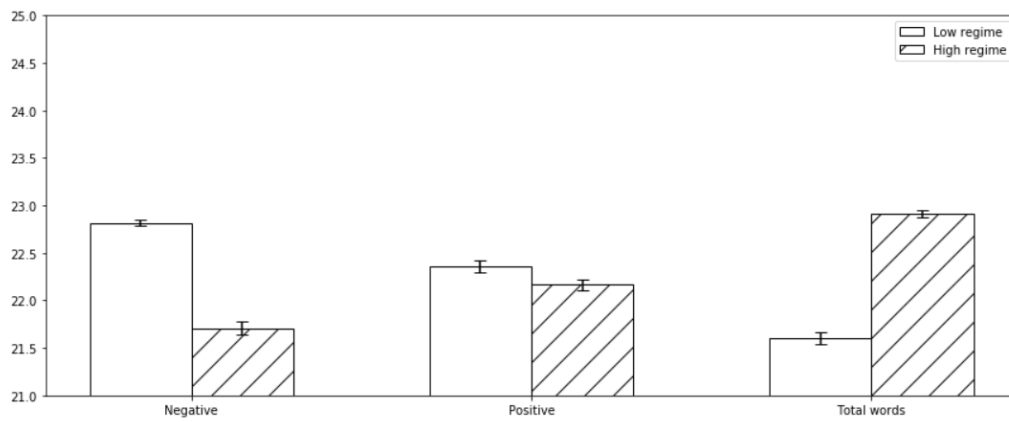
FIGURE 5.2: Time-varying between Bitcoin prices and negative sentiment.

We examined Bitcoin's average returns and average trading volume under two regimes (low and high states compared to median values). Figure 3 shows no significant difference in average Bitcoin returns between low and high regimes. It is statistically insignificant that average Bitcoin returns during high negativity exceed those in the low regime. This effect seems to be the opposite for positive states. Negative and positive sentiments in Trump's tweets and the number of words seem to drive Bitcoin trading volumes, but effects differ significantly during periods of above-average and below-average occurrence of positive and negative words. Our findings endorse Kaminski (2014), who correlates Bitcoin trading volume and sentiments expressed by 57,727 unique Twitter users. The effect of Twitter sentiment on Bitcoin trading volumes is indicated as 'speculative' (Kaminski, 2014; Shen, Urquhart, and Wang, 2019).

Preliminary data analysis provides three conclusions. First, there is no correlation among variables denoting negative, positive, and total words in Trump's tweets. Second, variables are not distributed normally. Third, given time fixed-effects, only trading volume reacts to regimes of above-average positivity and negativity. Fluctuations in Bitcoin returns are statistically insignificant during both regimes.



(A) Average return



(B) Average trading volume

FIGURE 5.3: Average return and trading volume under two regimes

5.5 Main findings

5.5.1 Regression and Causal relationship

Table 5.2 shows the impact of Trump's sentiment on contemporaneous Bitcoin returns. To our surprise, coefficients for contemporaneous sentiment are insignificant. Only negative sentiment correlates significantly and positively with Bitcoin returns at 5%. These findings indicate that increases in Bitcoin prices correlate to Trump's negative sentiments with a one-day lag. A 1% increase in negative sentiment is associated with a next-day increase of 11.0% to 11.7% in Bitcoin prices, depending on the regression considered. Then, Shen, Urquhart, and Wang (2019) indicated Twitter does not predict Bitcoin returns, but our negative coefficients are significant at 5%. Differences in method and research question explain the disparity in findings. Previous studies employ the number of times the term 'Bitcoin' which is tweeted (@BitinfoCharts) and capture investor sentiment. We consider the sentiment of Trump's tweets.

TABLE 5.2: Impact of Trump's sentiment on contemporaneous Bitcoin returns

Variables	(1) $BTC_{(t)}$	(2) $BTC_{(t)}$	(3) $BTC_{(t)}$	(4) $BTC_{(t)}$
$Negative_{(t)}$	-0.039 [-0.588]			-0.064 [-0.986]
$Positive_{(t)}$	-0.031 [-0.435]			-0.023 [-0.283]
$Total\ words_{(t)}$	-0.0001 [-0.053]			-0.0001 [-0.237]
$Negative_{(t-1)}$		0.110** [1.993]		0.117** [2.038]
$Positive_{(t-1)}$		-0.062 [-0.819]		-0.061 [-0.711]
$Total\ words_{(t-1)}$		0.002 [1.026]		0.002 [1.086]
$Negative_{(t-2)}$			0.054 [0.606]	0.031 [0.347]
$Positive_{(t-2)}$			0.026 [0.298]	0.022 [0.250]
$Total\ words_{(t-2)}$			-0.0001 [-0.030]	-0.001 [-0.353]
Observation	1071	1070	1069	1053
Adjusted R-square	0.004	0.005	0.003	0.007
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents OLS regression estimation results. The dependent variable is contemporaneous Bitcoin returns. We use variance inflation factors (VIFs) to check for multicollinearity. Because average mean VIF values for all variables (around 2.45) are well below the threshold of 10, we find no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020).

TABLE 5.3: Impact of Trump's sentiment on daily contemporaneous Bitcoin volume

Variables	(1) $Volume_t$	(2) $Volume_t$	(3) $Volume_t$	(4) $Volume_t$
$Negative_{(t)}$	-8.676*** [-2.909]			-6.474*** [-2.583]
$Positive_{(t)}$	0.304 [0.185]			-0.315 [-0.184]
$Total\ words_{(t)}$	-0.020 [-0.564]			-0.002 [-0.057]
$Negative_{(t-1)}$		-9.195*** [-3.207]		-7.396*** [-2.998]
$Positive_{(t-1)}$		0.363 [0.229]		0.086 [0.053]
$Total\ words_{(t-1)}$		-0.037 [-1.035]		-0.025 [-0.676]
$Negative_{(t-2)}$			-8.867*** [-3.137]	-6.934*** [-2.993]
$Positive_{(t-2)}$			0.893 [0.585]	1.697 [1.201]
$Total\ words_{(t-2)}$			-0.059 [-1.608]	-0.057 [-1.518]
Observation	1071	1070	1069	1053
Adjusted R-square	0.714	0.714	0.720	0.734
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volume. We use VIFs to check for multicollinearity. Because average mean VIF values for all variables (1.58) are well below the threshold of 10, we find no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020). Concomitantly, we also control the daily Bitcoin return to predict the Bitcoin volume.

Among surprising results in Table 5.3, trading volume declines when Trump's tweets contain more negative words. Moreover, the decline in trading volume contrasts with positive returns under uncertainty regimes. This counterintuitive finding also manifests among conventional asset classes. However, when Bitcoin prices rise, bid-ask spreads widen when Trump tweets more negative words. That finding indicates sellers incorporate greater uncertainty premiums (lower bids, higher ask prices) into immediate trades. This behavior seems not to apply to traditional financial assets, but Aalborg, Molnár, and Vries (2019) and Koutmos (2018b) demonstrated it is commonplace for cryptocurrency when Bitcoin trading volume declines during uncertainty. By approaching the microstructure of Bitcoin characteristics, we explain at 1% significance why negative Trump tweets induce positive returns as volumes decline.

TABLE 5.4: Impact of Trump's sentiment on monthly contemporaneous BTC volatility

Variables	(1) $Volatility_t$	(2) $Volatility_t$	(3) $Volatility_t$	(4) $Volatility_t$
$Negative_{(t)}$	-0.818* [-1.859]			-1.083** [-2.093]
$Positive_{(t)}$	-0.366 [-0.383]			-0.634 [-0.673]
$Total\ words_{(t)}$	-0.010 [-1.479]			-0.014 [-1.611]
$Negative_{(t-1)}$		-0.506 [-1.204]		-0.556 [-0.995]
$Positive_{(t-1)}$		0.721 [0.888]		-0.897 [-1.205]
$Total\ words_{(t-1)}$		-0.005 [-0.941]		
$Negative_{(t-2)}$			0.384 [0.996]	1.383** [2.314]
$Positive_{(t-2)}$			0.192 [0.326]	-0.105 [-0.171]
$Total\ words_{(t-2)}$			-0.006 [-1.066]	
Observation	37	36	35	35
Adjusted R-square	0.139	0.112	0.137	0.377
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volatility. Variance inflation factors (VIFs) confirm that the first and second lagged of total words exhibit multicollinearity with contemporaneous total words ($VIF > 10$). Therefore, we excluded those variables from the regression (4). Average mean VIF values (2.88) for all variables are well below the threshold of 10, indicating no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Lag length of one period is determined by the Schwarz Bayesian information criterion; we examine two days for further insights. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020). Concomitantly, we also control the average Bitcoin return to predict the Bitcoin volume.

Table 5.4 depicts the predictive power of Trump's tweets on Bitcoin volatility. Unlike Shen, Urquhart, and Wang (2019) we find at 5% significance that volatility correlates positively with a two-day lag in the variable denoting Trump's attitudes towards negative tone, and that variable with contemporaneous term correlates negatively with volatility. In our study, we referred to the previous empirical evidence from Huynh, Wang, and Vo (2021), which estimated the realized monthly volatility by taking the deviation from the daily price in one month. Interestingly, this study also found that a high level of global economic policy uncertainty could negatively predict Bitcoin volatility. One of the possible explanations is the bid-ask spread, which implies their risk aversion. Our findings are also consistent with the sound theory by Arrow (1959) and Bernanke (1983). Accordingly, the investors tend to wait and see under a high level of uncertainties. Concomitantly, we also used the approach of GARCH-in-mean (M-GARCH) to capture Bitcoin volatility. We also found that Trump's negative sentiment (contemporaneous and lagged terms) could negatively predict Bitcoin volatility (See in Appendices Figure D.1 and Table D.1). The results still hold when using Threshold-GARCH (T-GARCH) (See in Appendices Figure D.2 and Table D.2)

Our findings support Aysan and Lau (2019) that changes in historical geopolitical risk data correlate positively with Bitcoin volatility at different quantiles. Therefore, our results also link to the conflicts, political instability, which is through the presidential political announcements, can significantly influence Bitcoin's realized volatility. All in all, Bitcoin's returns, volatility, and trading volumes respond to the sentiment of Trump's tweets, especially, when it is negative.

TABLE 5.5: Vector Autoregressive Granger causality

Granger causality	χ^2
Negative sentiment does not Granger cause Return	1.20
Positive sentiment does not Granger cause Return	0.47
Total words do not Granger cause Return	0.92
Negative sentiment does not Granger cause Volume	2.35
Positive sentiment does not Granger cause Volume	2.09
Total words do not Granger cause Volume	0.68
Negative sentiment does not Granger cause Volatility	8.95***
Positive sentiment does not Granger cause Volatility	0.45
Total words do not Granger cause volatility	0.62

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The lag length is determined by the Schwarz Bayesian information criterion as one-level.

To test for causal relationships among positive sentiment, negative sentiment, and total words, we employ VAR Granger causality (Granger, 1969). In Table 5.5 the sentiment of Trump's tweets influences volatility, not returns and volume. Like Shen, Urquhart, and Wang (2019), we confirm a causal relation between tweeting and Bitcoin volatility, but we find none with respect to returns and volume.

5.5.2 Spillover effects of Trump's sentiment on Bitcoin market

Table 5.6 decomposes indices for the spillover effects of the sentiment in Trump's tweets on Bitcoin. In particular, the negative sentiment contributes more to Bitcoin's returns than the positive sentiment. However, OLS estimations reveal no significant coefficients. In addition, a pairwise comparison of spillovers and volatility indicates that positive sentiments in Trump's tweets induce greater daily volatility. The number of words spills over onto returns but not volatility.

TABLE 5.6: Trump sentiment and long-term spillovers on volatility

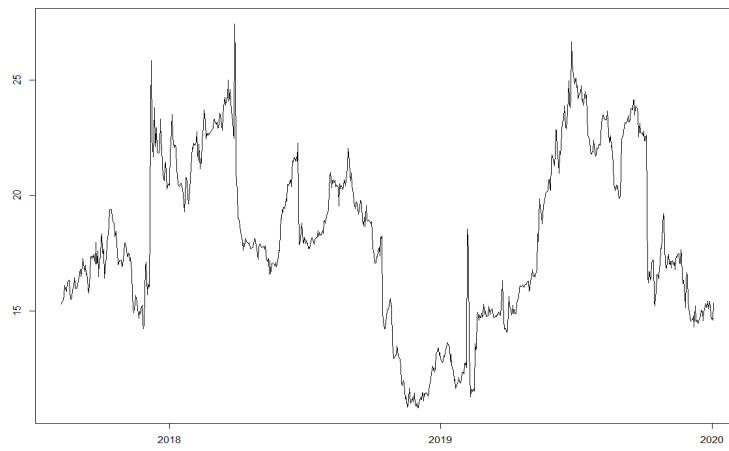
	Return	Volume	Negative	Positive	Total
Return	25.74	0.17	0.13	0.01	0.03
Volume	7.8	89.75	0.11	0.67	0
Negative	0.35	3.23	32.09	0.25	0.09
Positive	0.19	0.9	0.57	27.91	0.98
Total	1.05	13.07	1.41	0.86	35.14

Notes: This table captures directional spillover from variable j to variable i with rows indicating spillovers on and columns indicating spillovers from. These columns contain net pairwise (i,j) -th spillover indices.

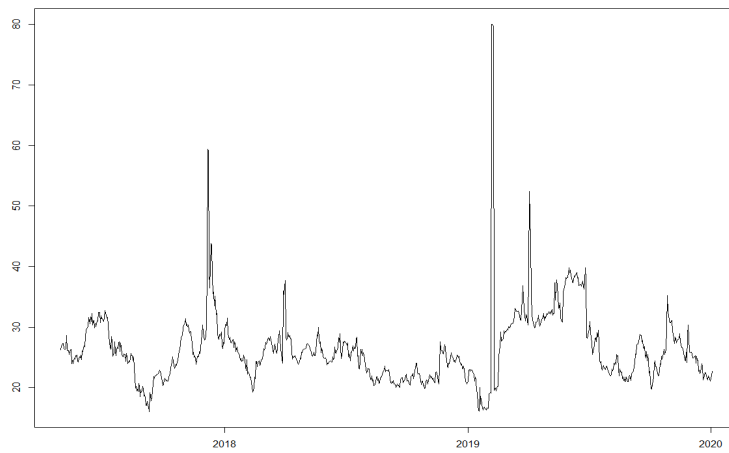
Figure 5.4 depicts the total volatility of spillover effects across three rolling windows in the time series (three years of daily data). It shows that the effects of Trump's tweets on Bitcoin were particularly high during the 2018 crash and early 2019. Overall, spillover effects are higher during shorter periods. Spillover is dramatic, presenting fluctuations of 30 to 80, during 50-day windows and less dramatic (fluctuations of 15 to 25) for longer periods. These findings indicate that the sentiment of Trump's tweets precipitates wide but fleeting short-term fluctuations on Bitcoin markets.

Ours is the first study to examine the effect of Trump's sentiment on Bitcoin markets using time-varying spillover effects. We find that Bitcoin digital currency is significantly affected by the political uncertainty raised by the politician. Although Bitcoin returns rise with the negative sentiment of Trump's tweets, this feature is challenged by the role of non-governmental control as well as safe-haven. Our findings confirm Jiang, Nie, and Ruan (2018) that the Bitcoin market is inefficient. The market is clearly not persistent in different rolling windows, which suggests investors should be cautious in presuming any arbitrarily beneficial opportunity or invest with only speculative intent. Our results also suggest Bitcoin's usefulness as a hedge due to heightened returns under Trump's negative sentiment. Fang et al. (2019) demonstrate that Bitcoin and equities correlate positively with economic policy uncertainty.

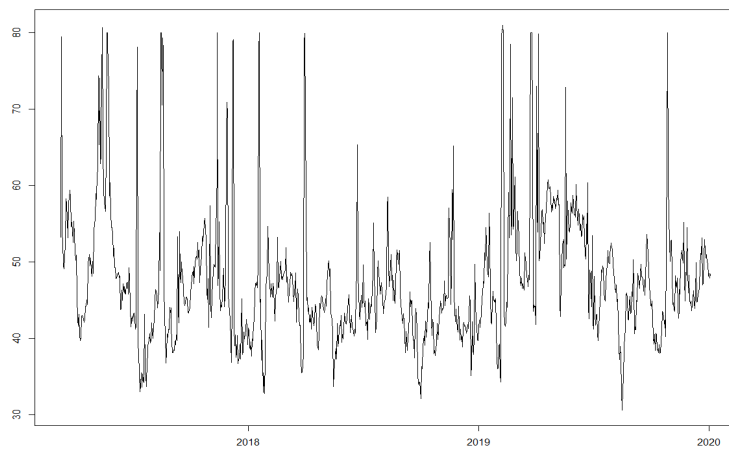
Figure 5.5 shows net spillover effects by component. Positive values indicate net contributors of spillovers and negative values its net recipients. The effects of Trump's



(A) 200-day



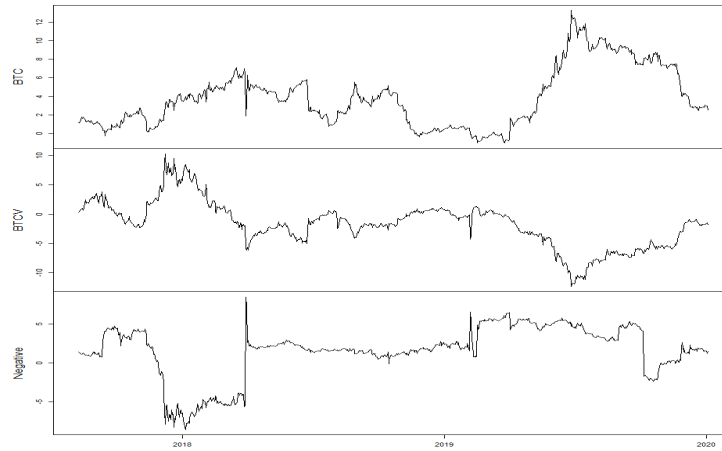
(B) 100-day



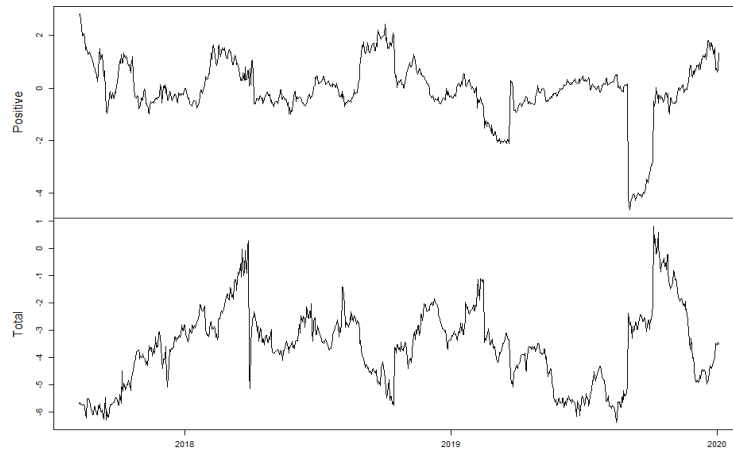
(C) 50-day

FIGURE 5.4: Time-varying spillover effects using a different-days rolling window

tweeted sentiments are weaker before 2019 and stronger after. In contrast, the positive sentiment and the total words are mostly recipient with time-varying values below 0.



(A) Return, Volume and Negative



(B) Positive and Total words

FIGURE 5.5: Net spillover effects by each component

5.5.3 Trump attitudes towards COVID-19 pandemic and Bitcoin

Recently, Rufai and Bunce (2020) confirmed the role of Twitter's G7 leaders in response to the COVID-19 pandemic because it should be considered as the potential source of information on the financial market. Concomitantly, the current literature indicates no linkage between feverish news and stock return changes but volatility (Ambros et al., 2020). However, the role of fake news, as well as investors' sentiment, play an important role (Huynh et al., 2021). Given the flow of Trump's tweets having responsive policies, this study extends the Trump's sentiment to examine whether this predictive factor holds robust during the pandemic time or not. We constructed the index of negative and positive sentiment by calculating the fraction of the number of negative words in tweets mentioning coronavirus (or COVID-19 pandemic, and so forth) over the total negative words on that day. It holds the same for positive sentiment. Finally, Table 5.7 represents the impact of Mr. President's attitudes towards the COVID-19 pandemic

on the cryptocurrency market.

TABLE 5.7: Impact of Trump's sentiment regarding COVID-19 on Bitcoin market

Variables	Return	Volatility	Volume
<i>COVID Negative</i> _(t)	-0.403* [-1.871]	-0.010 [-0.123]	0.527 [1.489]
<i>COVID Positive</i> _(t)	0.064* [1.929]	-0.013 [-0.858]	-0.144 [-0.500]
<i>Total words</i> _(t)	0.003 [1.000]	0.002 [0.501]	0.044 [1.318]
<i>COVID Negative</i> _(t-1)	0.010 [0.424]	0.046 [0.706]	-0.021 [-0.258]
<i>COVID Positive</i> _(t-1)	-0.011 [-0.499]	-0.003 [-0.084]	0.364* [1.884]
<i>Total words</i> _(t-1)	-0.002 [-0.746]	-0.004 [-0.701]	0.035 [1.170]
<i>COVID Negative</i> _(t-2)	0.005 [1.109]	0.000 [0.010]	0.232* [1.798]
<i>COVID Positive</i> _(t-2)	0.031 [1.432]	-0.002 [-0.053]	0.213 [0.885]
<i>Total words</i> _(t-2)	0.000 [0.087]	0.001 [0.354]	0.078*** [2.640]
Constant	-0.060 [-0.221]	-0.011 [-0.029]	65.750*** [17.980]
R-squared	0.219	0.02	0.394
Time-effect control	Yes	Yes	Yes

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The lag length is determined by the Schwarz Bayesian information criterion as one-level. This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volume. We use VIFs to check for multicollinearity. Because average mean VIF values for all variables (less than 2.0) are well below the threshold of 10, we find no evidence for multicollinearity. Robust standard deviations are in parentheses. The daily sample covers the period from December 2018 to October 2020. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020). In addition, we used the Bitcoin return to control the predictive regression model for volume and volatility.

While the current literature emphasizes the role of media coverage on financial markets during the COVID-19 time (Haroon and Rizvi, 2020), our findings also contribute to the existing literature that the country leader's attitudes could predict the Bitcoin market. Accordingly, the higher the pessimistic (optimistic) sentiment, the lower (higher) Bitcoin's expected return. Differing from the previous findings, we offer an insight that the Bitcoin market reacts immediately (contemporaneous time) instead of a one-day lagged term. However, we also obtain weak evidence that Trump sentiment is associated with the changes in Bitcoin returns at 10% significance level.

Concomitantly, we do not find any evidence that Trump's attitudes towards pandemic could predict the volatility while the Bitcoin volume is likely to respond to Donald Trump's sentiment in COVID-19 from one to two lagged days at 10% significance level.

Therefore, our findings confirm the extant literature that sentiment plays a role in improving market liquidity (Burggraf et al., 2020; Liu, 2015). To sum up, the cryptocurrency market reacts like the financial assets when the President's sentiment changed during the pandemic. To be more precise, it requires more (less) risk premium when having negative (positive) feelings from the leader; however, the sentiment is not the source of risk in this period. Our findings also contribute empirical evidence to the ongoing studies about financial markets and COVID-19.

5.5.4 Do Trump's Tweets trigger the Bitcoin jumps?

In this section, we examine whether Trump's tweets could predict the Bitcoin jumps. We employed the asymptotic distribution theory for a few non-parametric tests of Barndorff-Nielsen and Shephard (2006) to construct the binary variables for "Positive jumps" and "Negative jumps" from the hourly return of Bitcoin. Table 5.8 represents how Trump sentiments correlate with the possibility of having a jump of Bitcoin. Interestingly, only negative sentiments could act as the predictive factor to the Bitcoin positive jumps. Accordingly, when Trump expressed his attitudes towards the negative tone in a contemporaneous period, it was less likely to have positive jumps at the same time. Although we did not find any predictive power of negative sentiment at time (t) on Bitcoin returns, we extended the further empirical evidence that Trump's pessimistic tone negatively correlated with the likelihood of jumps having positive returns. Concomitantly, the higher (lower) return is associated with the higher (lower) possibility of having positive (negative) jumps. However, a decrease in trading volume could increase in the chance of facing new jumps in the largest capitalization cryptocurrency.

5.5.5 Robustness check

To examine whether the sentiment of Trump's tweets affects other cryptocurrencies, we substituted Bitcoin data with data for Ethereum (See in Appendix D.3). Again, we find an association between Ethereum's returns and a one-day lag in sentiment. Negative sentiments relate to lower same-day trading volume and with lags of one and two days. However, we find no Granger causality between Trump's sentiment and Ethereum's returns, trading volume, and volatility. Overall, our findings are still persisted when replacing different cryptocurrency assets. In addition, we employed the predictive regression model to test a relationship between the Trump sentiment and persistent variation in risk. We also found that Trump sentiments positively predict this ratio, representing the aggregate source of risk in the economy (Huang and Kilic, 2019). Hence, the possible channel of Trump's sentiments in predicting the future Bitcoin return could be the market risk (Huynh, Burggraf, and Wang, 2020) (See in Appendix D.4).

TABLE 5.8: The predictive power of Trump's Tweets on the Bitcoin's jumps

Variables	Positive Jumps	Negative Jumps
BTC Return	23.433*** [8.297]	-29.895*** [-8.181]
BTC Volume	-0.227* [-1.701]	-0.527*** [-3.412]
$Negative_{(t)}$	-17.282** [-2.123]	-3.436 [-0.677]
$Negative_{(t-1)}$	-5.601 [-0.727]	-13.515 [-1.431]
$Negative_{(t-2)}$	-6.156 [-0.863]	-1.492 [-0.163]
$Positive_{(t)}$	0.457 [0.080]	-0.645 [-0.086]
$Positive_{(t-1)}$	-2.018 [-0.333]	-3.252 [-0.485]
$Positive_{(t-2)}$	6.409 [0.926]	1.669 [0.282]
$Total\ words_{(t)}$	-0.183 [-1.348]	-0.145 [-0.894]
$Total\ words_{(t-1)}$	0.253* [1.709]	-0.047 [-0.322]
$Total\ words_{(t-2)}$	0.082 [0.594]	-0.058 [-0.384]
Constant	-19.303* [-1.747]	-56.822*** [-4.471]
Time-effect control	Yes	Yes
Pseudo R-squared	0.128	0.175

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. This table presents estimations from the Logit regression. The dependent variable receives binary values (1 - jumps detected and 0 - otherwise). Robust standard deviations are in parentheses. The daily sample covers the period from January 2017 to January 2020. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020). In addition, we used the Bitcoin return and Bitcoin volume to control the predictive regression model for the Bitcoin jumps.

5.6 Conclusion

This paper has explored relations between Bitcoin's returns, volatility, and trading volumes and the positive or negative sentiments expressed in tweets by the US President Donald J. Trump. We find that the sentiment of Trump's tweets reasonably predicts Bitcoin's returns, volatility, and trading volumes. The more negative Trump's sentiment, the higher returns. However, volatility diminishes when Trump tweets negative sentiments. The trading volume rises with lags of two days and declines contemporaneously. Only volatility and negativity exhibit Granger-causal relationships.

Although Donald Trump is no longer the US President, this study still has some merits. First, this is the first study to offer a relationship between textual analyses in social media account of politician and cryptocurrency markets. Our study also challenges the concept that these coins are independent of the political risk (or any uncertainties arising from the specific government). After controlling the rigorous variables, we found that one Twitter account, particularly the US President, could drive the cryptocurrency markets. This is the typical case of Elon Musk, the richest man in the world (Ante, 2021), who can be an influential and well-known individual on the cryptocurrency market. In doing so, future research could explain how other politicians' and billionaires' social media accounts could drive the cryptocurrency markets. Second, this paper also discusses the evolution of cryptocurrency markets' behaviors during the pandemic crisis. To be more specific, in normal times, cryptocurrency exhibits its own characteristics in response to the uncertainties. However, in the crisis time, cryptocurrency is likely to respond as the traditional financial assets. Also, future research can consider how cryptocurrencies change during the specific period in their development. Finally, we also found that Trump's tweets with pessimistic feelings could predict the Bitcoin's jumps; therefore, this paper contributes the predictive feature of Trump's tone on how Bitcoin returns jump during the 2017-2020 period. Accordingly, professional traders could keep their eyes on the content on social media to predict when and how Bitcoin exhibits large movements in its return.

We find evidence of time-varying spillover effects between Trump's sentiments and Bitcoin prices. Longer periods showed lower spillovers in volatility than shorter periods, indicating that the short-term effects of Trump's tweets are greater than their long-term effects. Additionally, the negative effect is most evident during periods of above-average and below-average occurrence of positive and negative words and the total number of words in Trump's tweets. We also find Bitcoin markets seem more sensitive to Trump's negative sentiments after 2018. This study employs daily data. Future studies might garner more insights using intra-day or tick-by-tick data with the existence of cryptocurrency uncertainty indices (Foglia and Dai, 2021b), or machine learning approach (Abdullah, 2021).

Chapter 6

Conclusion

This dissertation comprises four individual essays which contribute to the existing literature in terms of “market reactions and cryptocurrency”. Since the detailed findings and results have been discussed in the previous chapters, only some key features and practical implications can be discussed in this concluding chapter. They can be summarized as follows.

In the first chapter, the causal relationships between political news and stock market reactions are examined. It finds that tweets related to the US-China trade war negatively cause S&P 500 returns and positively cause VIX. The effects of political news on social media are heterogeneous across industries depending on their level of trade openness with China. The second essay provides an industry-level analysis of the market reaction to sudden COVID-19 news announcements in the United States. The results indicate that the market significantly reacts before February 26. More precisely, medical and pharmaceutical products have a positive reaction while restaurants, hotels, motels, and services and utilities show the opposite finding. Furthermore, this study also exhibits the relationship between the searching term (‘coronavirus’), the level of investor attention to COVID-19, and industry returns. The following two chapters are a collection of a cryptocurrency study. The third chapter investigates the prediction power of the ratio of gold to platinum prices (GP) on the cryptocurrency market. Since this ratio has been used as the aggregate market risk to predict the expected stock return, bond premium, this study provides a piece of empirical evidence that the Bitcoin (even alternative coin - Ethereum) return goes up when having a relative increase in the price of gold to platinum. This study also employs different methodologies, a sub-sample test for the special period with a significant increase in gold prices, and the different data sources to validate the results. Eventually, our results hold robust. The last chapter applies the textual analysis and spillover estimations to study whether the sentiment expressed in the US President’s tweets is associated with the changes in price, volatility, and trading volume in the cryptocurrency market. After analyzing 13,918 tweets over 4-year starting from 2017, this work found that only negative sentiment had the predictive power on Bitcoin returns, trading volumes, realized volatility, and jumps. By introducing a novel methodology (spillover connectedness) and constructing the social media sentiment index for the market risk, it demonstrates that Trump’s Twitter sentiment can impact the Bitcoin market in the form of time-varying dependence. I

also carry out further analysis, particularly in the COVID-19 pandemic, and find that his attitudes towards the coronavirus also have predictive power on the Bitcoin market. Likewise the previous chapter, our findings are persisted when replacing the alternative coin (Ethereum).

Overall, the results documented in this dissertation contribute to the ongoing literature in finance. Whether political uncertainty affecting economic activity is currently a debatable topic. It seems stunning that politicians' pronouncements on social media could instantly create or wipe off hundreds of billions of dollars from the financial market. Obviously, after the global financial crisis 2007-2008, the world is more likely to experience more uncertainties from many different aspects. This news can be from the withdrawal of the United Kingdom (UK) from the European Union (EU) (called BREXIT), the conflicts in terms of trade between the United States and China, the intense criticism about immigration, and so forth. Concomitantly, the world has suffered from the unprecedented event, coronavirus outbreak (also known as COVID-19 pandemic). These critical events partially reflect how life happens in the contemporary era. Significantly, this concept is also linked with technological advancement when political news can be immediately released on the Internet. In addition, life is changing with quickly measuring how people pay their attention to the simple 'click' on the Google website. Taken together, the two first chapters provide evidence that gives more complete pictures of how the market swings with political news leaked by tweets or public health announcements confirmed by the official organization (for example, WHO). Hence, this study explains that the continuous flow of crucial news in this era leads investors to update their beliefs in investing strategies in the future. As with other aspects of news, time will tell whether these beliefs are justified. Therefore, this thesis tries to fill this gap to study how contemporaneous events could influence the financial markets. Another noteworthy contribution is provided with regards to the examination of the insights about the cryptocurrency market. The topic of cryptocurrency return predictability at the aggregate market risk is of great interest to both scholars and practitioners. Due to the incomplete literature on the intrinsic value of cryptocurrencies, this study provides empirical evidence to validate the ratio of Gold and Platinum prices in the digital currency world. Being the first study to investigate the predictive power of this ratio on this market, this work does not only validate the existing literature but also shed a new light on the prediction model in the cryptocurrency market. The previous evidence has been focused on equity and fixed-income markets. This study complements the current literature by explaining how cryptocurrencies are sensitive to macroeconomic shocks, showing that these coins should be considered as investing assets. Finally, the last academic chapter highlights the role of sentiment in the cryptocurrency market. Although traditional finance suggests that investor sentiment can explain the stock's price based on the divergence of price from its fundamental value, there is still a space for this market. However, there is little research on the politician's sentiment. This is somewhat surprising given the US President's leakage of

information or announcements as the potential risks. Then, the investors might absorb information with overly optimistic or pessimistic attitudes, partially leading to irrational investment decisions. Thus, this final study proposes a new textual disclosure tone-based politician perspective that might contain incremental sentiment information beyond other market participants. The result is part of a new stream of literature using the big text data on Twitter to capture three potential tones of Mr. Donald Trump, which significantly predict the cryptocurrency market. A realistic and straightforward explanation for this finding is that the role of cryptocurrencies in the financial world has not yet been confirmed. They can be treated as an electronic payment tool, an investment, a safe-haven asset, a hedging instrument, or even a diversifier. Overall, it seems extremely difficult for our empirical results to assess due to the anonymity and decentralized trading system transparently. Among potential mechanisms, academics and industry-sector respondents viewed that Bitcoin and other alternative cryptocurrencies were more likely to listen to the fundamental economic news.

With regards to practical implications, the findings in this thesis are of interest to different stakeholders, policymakers, financial analysts, investment professionals. Journalists used to describe Donald J. Trump with the strongest tone. Bigot. Racist. Trumpedy.¹ The superlatives are not all bad. Trump's presidency can be considered a natural experiment to measure the impacts of unofficial news on financial markets. This point holds to the COVID-19 pandemic. There is a great deal of fake news, conspiracy theory, and fears during these special times. Thus, resolving information asymmetries from a wide range of information sources (social media, the White House) is the first implication for policymakers. It is worth stressing that the world will have more unexpected news and events, widening the gap of asymmetric information. Concomitantly, the mechanisms of supervising unexpected news should be implemented from the authority perspective. From the investors' standpoint, the results contribute to the market reactions based on different sources of news. Thus, the investment professionals should keep their eyes on the market, which might help identify the unexpected news to avoid losses or make profits from the market expectations. Clearly, financial analysts could incorporate these types of news as financial indicators to improve the current models. Given the brash, petulant and unpredictable content from Donald J. Trump's Twitter and the unprecedented and unique event from the COVID-19 pandemic, some could probably challenge whether my results are generalizable. In this respect, this thesis could generate the trend and tendency of using social media as pass-through policies in the US. Furthermore, what we know about COVID-19 might be applicable for the future pandemic. At any rate, the results certainly provide unique insight to the certain merits of financial markets in the contemporary era. As regards the two last chapters, research on the cryptocurrency market in finance is still in its beginning. Therefore, exploring two predictive indicators, such as Gold-Platinum and Trump's sentiment, could help understand the market structure of cryptocurrency. In

¹See more at [Trump is an embarrassment](#) by CNN.

doing so, the algorithms and prediction model should include these elements to capture the cryptocurrency movements. The techniques developed in this thesis can be used in building more indices, captured the sentiment from other well-known social media accounts such as Elon Musk, CZ (the founder of Binance exchange), and so forth as new market participants are added. By shedding light on predicting Bitcoin with the aggregate market risk, this thesis hopes to explain the Bitcoin characteristic as an investment tool, thereby allowing more investing decisions that weigh up the benefits and costs under the specific market periods (growing time or distress).

Finally, this doctoral thesis moves the literature closer to answering the crucial role of news and announcements on market reactions on the onset of pandemic and technological integration. Additionally, the validity of predictive indicators, including the precious metals or digital content, could potentially explain the cryptocurrency characteristics. With the more frequent data, especially tick-by-tick or each minute, another interesting avenue for future research would be to model how long the market reacts after these types of news. The future study might employ state-of-the-art hybrid deep learning to improve the quality of textual analysis. From the standpoint of practitioners, these approaches could substantially improve their financial decision-making in both the conventional and cryptocurrency markets.

Appendix A

Political news and stock prices: Evidence from Trump's trade war

This section is based on Burggraf, T., Fendel, R., Huynh, T. L. D. (2020). Political news and stock prices: evidence from Trump's trade war. *Applied Economics Letters*, 27(18), 1485-1488.

To assess the robustness of our results, we create a 'placebo' tweet variable including tweets from Donald Trump that mention China but which are not related to the US-China trade war. Performing the same VAR-Granger causality analysis, we do not find any evidence that placebo tweets significantly influence S&P 500 return or VIX. Finally, we apply our model to the Dow Jones Industrial Average index. The robustness tests can be found in Tables [A.1](#) – [A.4](#).

TABLE A.1: Robustness Test: Vector autoregressions with Placebo Tweet

Variables	$Return_{(t)}$	$VIX_{(t)}$	$PlaceboTweet_{(t)}$
$Return_{(t-1)}$	0.471*** (0.11)	-0.634 (14.36)	-3.716 (2.80)
$Return_{(t-2)}$	-0.131 (0.10)	0.275 (14.00)	-3.379 (2.73)
$VIX_{(t-1)}$	0.002*** (0.00)	-0.001 (0.10)	0.008 (0.02)
$VIX_{(t-2)}$	-0.001 (0.00)	-0.121 (0.09)	-0.044 (0.02)
$PlaceboTweet_{(t-1)}$	-0.001 (0.00)	0.41 (0.31)	0.035 (0.06)
$PlaceboTweet_{(t-2)}$	-0.003 (0.00)	0.196 (0.31)	0.077 (0.06)

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Control variables are used. Robust standard errors in parentheses.

TABLE A.2: Robustness Test: Granger causality tests with Placebo Tweet

Variable	Null hypothesis 1	
	F-statistics	p-value
Return	1.7295	0.421
VIX	2.1047	0.349

Note: *** p < 0.01; ** p < 0.05; * p < 0.10.

TABLE A.3: Robustness Test: Vector autoregressions with the Dow Jones

Variables	$Return_{(t)}$ Dow Jones	$VIX_{(t)}$	$Trump\ Tweet_{(t)}$
$Return_{(t-1)}$	0.394*** (0.103)	6.348 (14.216)	-2.344 (3.387)
$Return_{(t-2)}$	-0.113 (0.100)	-6.340 (13.888)	4.359 (3.309)
$VIX_{(t-1)}$	0.001*** (0.001)	0.032 (0.098)	-0.001 (0.023)
$VIX_{(t-2)}$	-0.001 (0.001)	-0.136 (0.092)	0.019 (0.022)
$Tweet_{(t-1)}$	-0.005*** (0.002)	0.585** (0.270)	0.250*** (0.064)
$Tweet_{(t-2)}$	0.003** (0.002)	-0.400 (0.270)	0.062 (0.064)

Note: *** p < 0.01; ** p < 0.05; * p < 0.10.
Control variables are used. Robust standard errors in parentheses.

TABLE A.4: Robustness Test: Granger causality tests with the Dow Jones

Variable	Null hypothesis 1	
	F-statistics	p-value
Return (Dow Jones)	10.029***	0.007
VIX	5.7574*	0.056

Note: *** p < 0.01; ** p < 0.05; * p < 0.10.

TABLE A.5: Industry test: Summary of VAR tests for industry

Variables	Electronic	Machinery	Transportation	Chemicals	Textiles	Minerals	Agricultural	Forest	Footwear	Energy
$Tweet_{(t-1)}$	-0.820*** [0.263]	-0.953*** [0.294]	-0.935*** [0.244]	-1.050*** [0.297]	-0.838*** [0.321]	-0.345* [0.183]	-0.498** [0.242]	-0.613* [0.346]	-0.697** [0.335]	-0.618** [0.307]
$Tweet_{(t-2)}$	0.34 [0.264]	0.418 [0.295]	0.225 [0.245]	0.207 [0.298]	0.359 [0.320]	0.438** [0.181]	0.333 [0.242]	0.081 [0.344]	0.459 [0.333]	0.361 [0.306]
VAR Granger causality	10.092***	11.003***	14.706***	12.490***	7.112**	7.793**	5.098*	3.163	5.218*	4.611*
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade openness (US-China)	220,542	62,716	57,146	49,552	45,880	41,715	28,085	17,333	14,357	9,577
% Trade	40.33%	11.47%	10.45%	9.06%	8.39%	7.63%	5.14%	3.17%	2.63%	1.75%

Note: *** p < 0.01; ** p < 0.05; * p < 0.10. Robust standard errors in brackets.

TABLE A.6: Industry test: Summary of SVAR tests for industry

Variables	Electronic	Machinery	Transportation	Chemicals	Textiles	Minerals	Agricultural	Forest	Footwear	Energy
$Tweet_{(t)}$ - Structural VAR	-0.653*** [0.062]	-0.677*** [0.060]	-0.655*** [0.064]	-0.552*** [0.056]	0.582*** [0.055]	-0.916*** [0.085]	-0.460*** [0.060]	0.437*** [0.051]	0.509*** [0.052]	-0.394*** [0.0512]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade openness (US-China)	220,542	62,716	57,146	49,552	45,880	41,715	28,085	17,333	14,357	9,577
% Trade	40.33%	11.47%	10.45%	9.06%	8.39%	7.63%	5.14%	3.17%	2.63%	1.75%

Note: *** p < 0.01; ** p < 0.05; * p < 0.10. Robust standard errors in brackets.

TABLE A.7: Industry test: Differences in return across industries

	Electronic	Machinery	Transportation	Chemicals	Textiles	Minerals	Agricultural	Forest	Footwear	Energy
Mean return (With Tweet)	-0.6833	-0.6833	-0.6833	-0.4084	-0.7478	-0.1595	-0.0682	-0.7436	-0.5118	-0.4365
Standard error	0.3431	0.3431	0.3431	0.3845	0.437	0.2147	0.0849	0.3867	0.3553	0.3377
Mean return (No Tweet)	0.0244	0.0244	0.0244	0.0474	0.0214	0.0421	-0.5206	0.2067	-0.1284	-0.0381
Standard error	0.0856	0.0856	0.0856	0.0989	0.1043	0.0622	0.2887	0.1148	0.1141	0.1085
T-statistics	2.7148***	2.7148***	2.7148***	1.5251	2.3951**	1.0989	1.8121*	2.8208***	1.1602	1.2679

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Appendix B

Did Congress trade ahead? Considering the reaction of US industries to COVID-19

This chapter is based on Goodell, J. W., Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. Finance Research Letters, 36, 101578, <https://doi.org/10.1016/j.frl.2020.101578>.

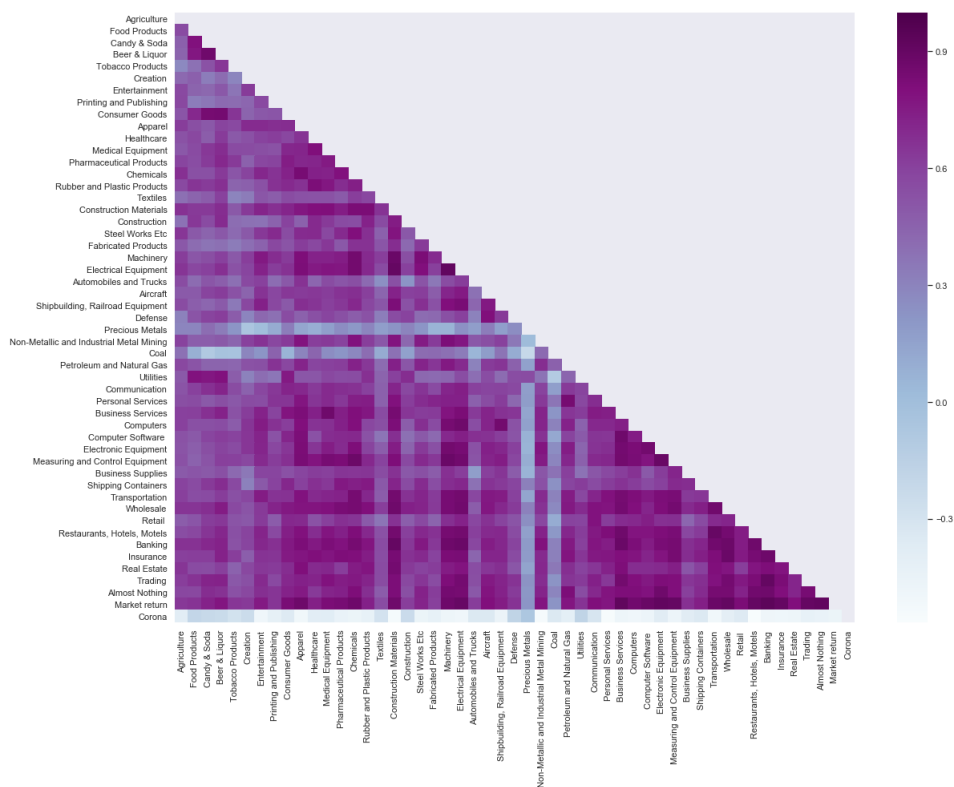


FIGURE B.1: Correlation matrix (Full sample).

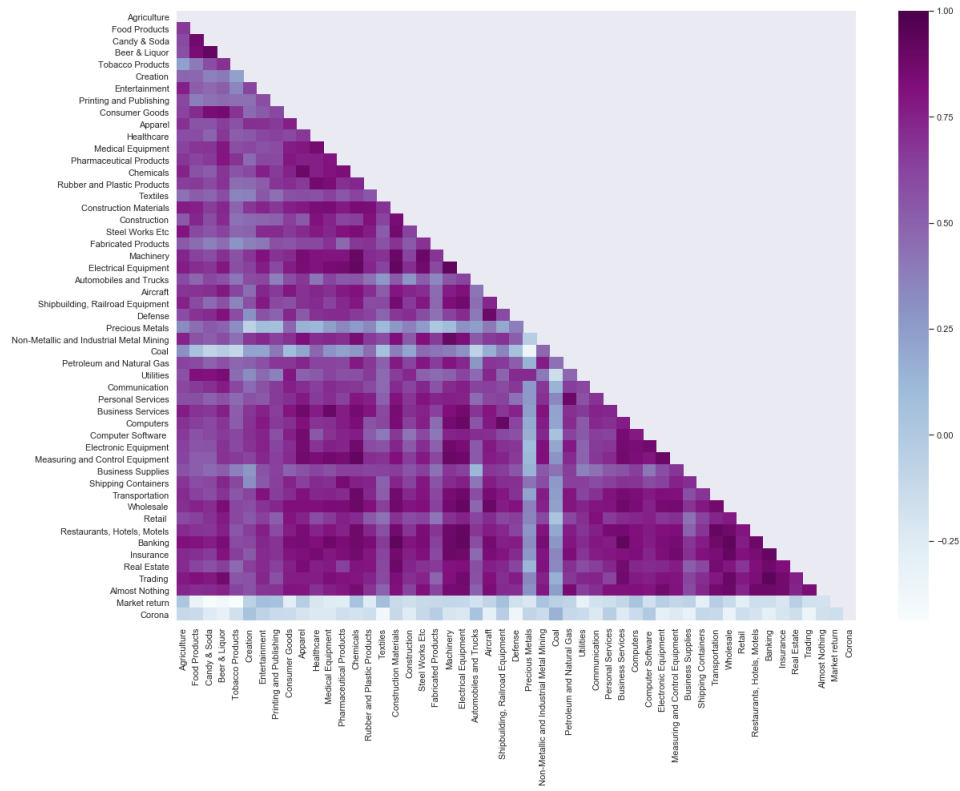


FIGURE B.2: Correlation matrix (After January 21, 2021).



FIGURE B.3: Correlation matrix (Before January 21, 2021).

Appendix C

Gold, Platinum, and expected Bitcoin returns

This chapter is based on Huynh, T. L. D., Burggraf, T., Wang, M. (2020). Gold, platinum, and expected Bitcoin returns. *Journal of Multinational Financial Management*, 56, 100628, <https://doi.org/10.1016/j.mulfin.2020.100628>.

TABLE C.1: Descriptive statistics for Ethereum and logGP

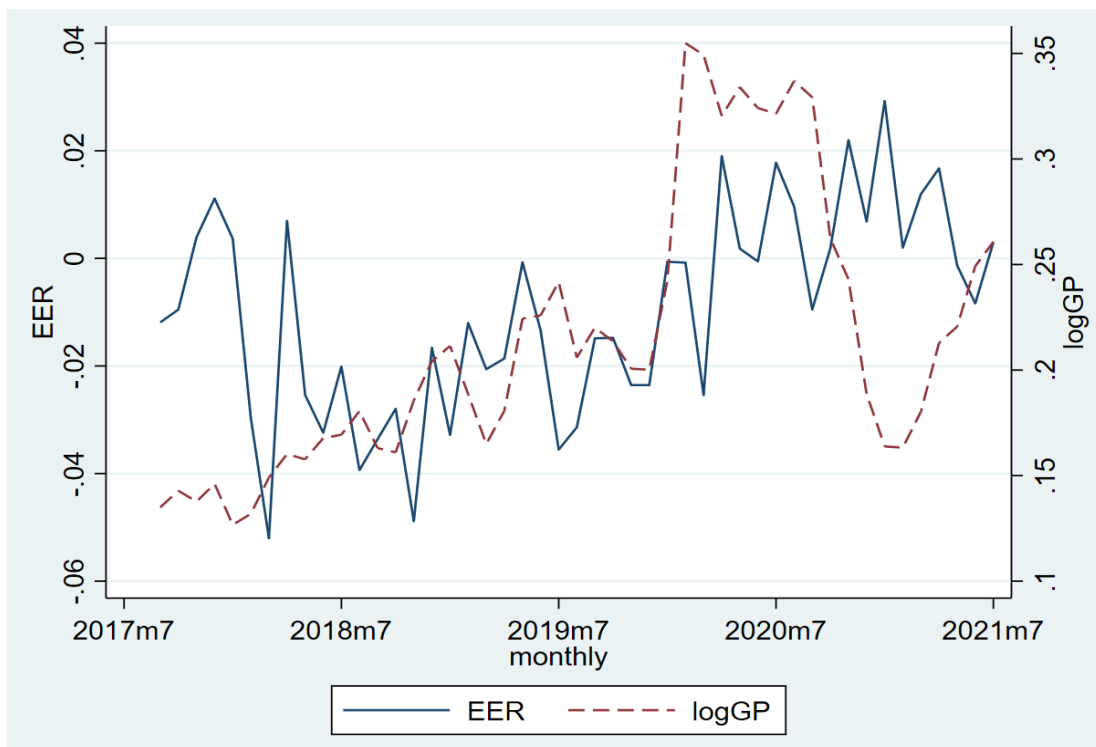
Variable	Mean	Std. dev.	Min	Max	KPSS	ADF
LogGP	0.214	0.065	0.127	0.355	0.445***	-3.881***
EER	-0.010	0.019	-0.052	0.029	0.316***	-1.614

Notes: The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. ADF stands for Dickey-Fuller stationary test. The monthly data from September 2017 to July 2021. EER is Excess Ethereum Return, calculated by the discrepancy between real Ethereum return and risk-free rate return of 3-month US Treasury bill. Gold fixing prices are collected from the London Bullion Market Association while platinum fixing prices are retrieved from London Platinum and Palladium Market. These data are daily and aggregated to monthly to avoid missing information. logGP was calculated by the natural logarithm of ratio between two metals' prices by monthly frequency.

TABLE C.2: Ethereum predictability by OLS with data from Bitstamp

Ethereum excess return	Monthly (Bitstamp)			
	1 month	3 month	6 month	12 month
logGP	0.0821**	0.158***	0.190***	0.149***
R^2	8.72	28.54	46.83	33.88
Time-effect control	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$; * $p < 0.1$. Excess Ethereum Return, calculated by the discrepancy between real Ethereum return and risk-free rate return of 3-month US Treasury bill. The robust OLS regressions are applied. The further estimations based on Newey and Kenneth (1987) with correcting the heteroskedasticity, autocorrelation consistent (HAC), and robust standard errors are consistent to our results.



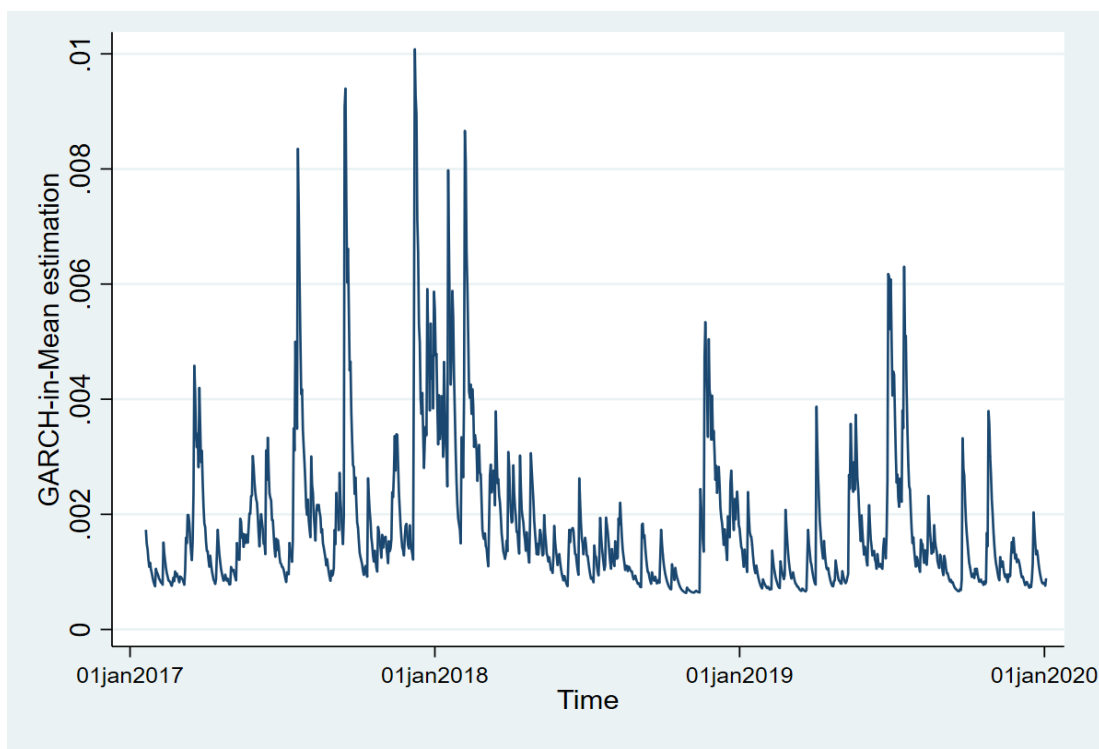
This figure shows the natural logarithm of the Gold-Platinum prices Ratio and Excess Ethereum Return from September 2017 to July 2021. Our data is monthly frequency.

FIGURE C.1: LogGP ratio and Excess Ethereum Return

Appendix D

Does Bitcoin react to Trump's Tweets?

This section is based on Huynh, T. L. D. (2021). Does Bitcoin React to Trump's Tweets?. *Journal of Behavioral and Experimental Finance*, 31, 100546, <https://doi.org/10.1016/j.jbef.2021.100546>



Notes: We employed the GARCH-in-Mean estimations to measure the Bitcoin volatility. This figure illustrates variance functions.

FIGURE D.1: Bitcoin volatility was estimated by the GARCH-in-mean (M-GARCH)

TABLE D.1: Impact of Trump's sentiment on Bitcoin volatility, captured by M-GARCH

Variables	(1) $Volatility_t$	(2) $Volatility_t$	(3) $Volatility_t$	(4) $Volatility_t$
$Negative_t$	-0.009** [-2.492]			-0.007** [-2.208]
$Positive_t$	0.002 [0.559]			0.001 [0.291]
$Total\ words_t$	-0.0001 [-1.049]			-0.0001 [-0.844]
$Negative_{t-1}$		-0.009*** [-2.609]		-0.007** [-2.247]
$Positive_{t-1}$		0.001 [0.428]		0.001 [0.403]
$Total\ words_{t-1}$		-0.0001 [-0.783]		-0.0001 [-0.438]
$Negative_{t-2}$			-0.010*** [-3.085]	-0.008*** [-2.917]
$Positive_{t-2}$			-0.000 [-0.128]	-0.000 [-0.044]
$Total\ words_{t-2}$			-0.0001 [-1.047]	-0.0001 [-0.966]
Observation	1071	1070	1069	1053
Adjusted R-square	0.05	0.05	0.053	0.07
Other control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volatility, estimated by using GARCH-in-Mean (M-GARCH). Variance inflation factors (VIFs) confirm that the first and second lagged of total words exhibit multicollinearity with contemporaneous total words (VIF > 10). Therefore, we excluded those variables from the regression (4). Average mean VIF values (1.58) for all variables are well below the threshold of 10, indicating no evidence for multicollinearity. Robust standard deviations are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Lag length of one period is determined by the Schwarz Bayesian information criterion; we examine two days for further insights. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020).

TABLE D.2: Impact of Trump's sentiment on Bitcoin volatility, captured by T-GARCH

Variables	(1) $Volatility_t$	(2) $Volatility_t$	(3) $Volatility_t$	(4) $Volatility_t$
$Negative_{(t)}$	-0.009** [-2.452]			-0.008** [-2.162]
$Positive_{(t)}$	0.002 [0.576]			0.001 [0.315]
$Total\ words_{(t)}$	-0.0001 [-1.028]			-0.0001 [-0.823]
$Negative_{(t-1)}$		-0.009*** [-2.589]		-0.007** [-2.221]
$Positive_{(t-1)}$		0.001 [0.433]		0.001 [0.406]
$Total\ words_{(t-1)}$		-0.0001 [-0.777]		-0.0001 [-0.437]
$Negative_{(t-2)}$			-0.010*** [-3.069]	-0.008*** [-2.895]
$Positive_{(t-2)}$			-0.0001 [-0.128]	-0.0001 [-0.047]
$Total\ words_{(t-2)}$			-0.0001 [-1.040]	-0.0001 [-0.960]
Observation	1071	1070	1069	1053
Adjusted R-square	0.04	0.05	0.053	0.07
Other control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volatility, estimated by using Threshold-GARCH (T-GARCH). Variance inflation factors (VIFs) confirm that the first and second lagged of total words exhibit multicollinearity with contemporaneous total words (VIF > 10). Therefore, we excluded those variables from the regression (4). Average mean VIF values (1.58) for all variables are well below the threshold of 10, indicating no evidence for multicollinearity. Robust standard deviations are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Lag length of one period is determined by the Schwarz Bayesian information criterion; we examine two days for further insights. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh, Burggraf, and Wang, 2020).

TABLE D.3: Impact of Trump's sentiment on contemporaneous ETH returns

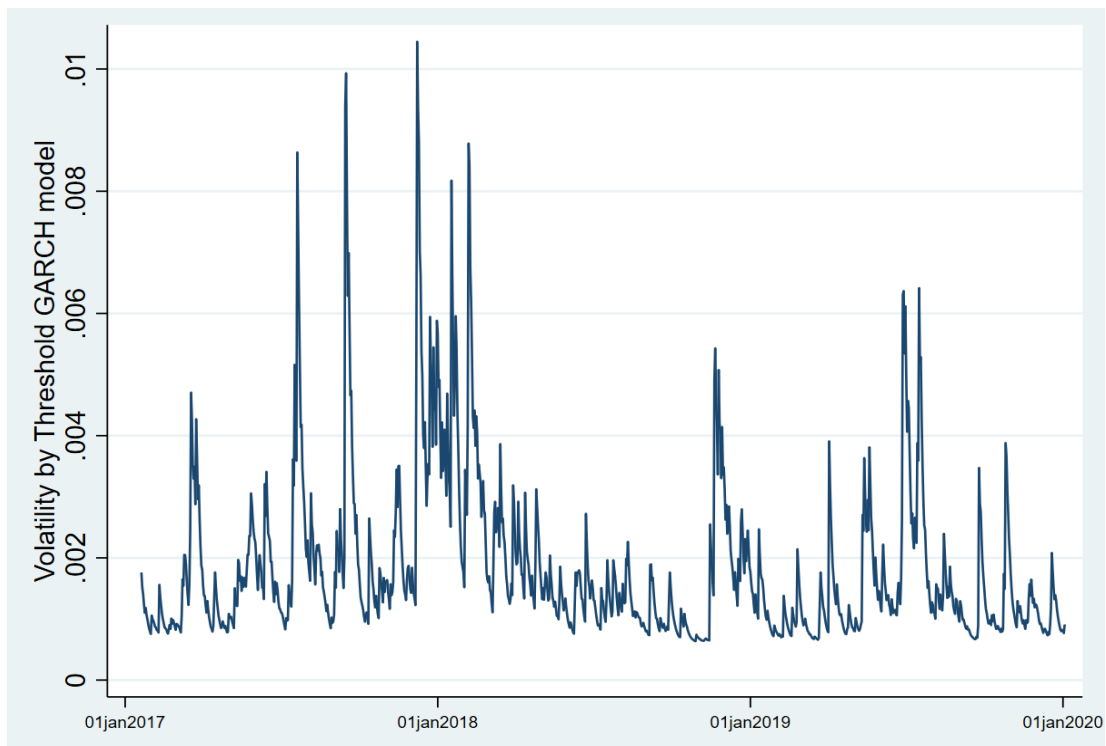
Variables	(1) ETH_t	(2) ETH_t	(3) ETH_t	(4) ETH_t
$Negative_{(t)}$	0.034 [0.403]			0.005 [0.061]
$Positive_{(t)}$	-0.155 [-1.261]			-0.144 [-1.054]
$Total\ words_{(t)}$	-0.003 [-0.910]			-0.002 [-0.675]
$Negative_{(t-1)}$		0.194** [1.972]		0.177* [1.798]
$Positive_{(t-1)}$		0.095 [0.782]		0.118 [0.867]
$Total\ words_{(t-1)}$		0.001 [0.453]		0.002 [0.722]
$Negative_{(t-2)}$			0.209 [1.423]	0.172 [1.195]
$Positive_{(t-2)}$			0.066 [0.395]	0.042 [0.247]
$Total\ words_{(t-2)}$			-0.003 [-1.136]	-0.003 [-1.167]
Observation	1071	1070	1069	1053
Adjusted R-square	0.01	0.01	0.02	0.02
Other control	Yes	Yes	Yes	Yes

Notes: This table presents OLS regression estimation results. The dependent variable is contemporaneous Ethereum returns. We use variance inflation factors (VIFs) to check for multicollinearity. Because average mean VIF values for all variables (around 1.98) are well below the threshold of 10, we find no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Ethereum from the previous literature (Huynh, Burggraf, and Wang, 2020) and the trading volume of Ethereum.

TABLE D.4: The predictive power of Trump sentiment on the ratio Gold-Platinum

Variables	(1) GP_t	(2) GP_t	(3) GP_t	(4) GP_t
$Negative_{(t)}$	-0.036 [-1.111]			0.077 [0.889]
$Positive_{(t)}$	0.061* [1.675]			-0.073 [-1.078]
$Total\ words_{(t)}$	-0.0003 [-0.355]			0.012*** [7.351]
$Negative_{(t-1)}$		-0.046 [-1.030]		-0.034 [-0.264]
$Positive_{(t-1)}$		0.014 [0.464]		-0.120* [-1.896]
$Total\ words_{(t-1)}$		-0.0001 [-0.178]		0.012*** [7.513]
$Negative_{(t-2)}$			-0.002 [-0.037]	0.168* [1.871]
$Positive_{(t-2)}$			0.004 [0.148]	0.024 [0.392]
$Total\ words_{(t-2)}$			-0.0004 [-0.505]	0.013*** [8.283]
Observation	767	761	760	755
Adjusted R-square	0.837	0.837	0.836	0.511
Other control	Yes	Yes	Yes	Yes

Notes: This table presents OLS regression estimation results. The dependent variable is contemporaneous ratio of Gold-Platinum. We use variance inflation factors (VIFs) to check for multicollinearity. Because average mean VIF values for all variables (around 1.47) are well below the threshold of 10, we find no evidence for multicollinearity. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Ethereum from the previous literature (Huynh, Burggraf, and Wang, 2020).



Notes: We employed the Threshold-GARCH estimations to measure the Bitcoin volatility. This figure illustrates variance functions.

FIGURE D.2: Bitcoin volatility was estimated by the Threshold-GARCH (T-GARCH)

Appendix E

Textual analysis code

This content is based on (Hutto and Gilbert, 2014).

```

1 import sys, string, re
2 import pandas as pd
3
4 lmdict = {'Negative': [' '],
5          'Positive': [' ']}
6
7 hdic = {'Negative': [' '],
8         'Positive': [' ']}
9
10 negate = [' ']
11
12
13 def negated(word):
14     if word.lower() in negate:
15         return True
16     else:
17         return False
18
19
20 def tone_count_with_negation_check(dict, article):
21
22     pos_count = 0
23     neg_count = 0
24
25     pos_words = []
26     neg_words = []
27
28     input_words = re.findall(r'\b([a-zA-Z]+n\ 't|[a-zA-Z]+\ 's|[a-zA-Z]+)\ 'b', article.lower())
29
30     word_count = len(input_words)
31
32     for i in range(0, word_count):
33         if input_words[i] in dict['Negative']:
34             neg_count += 1
35             neg_words.append(input_words[i])
36         if input_words[i] in dict['Positive']:
37             if i >= 3:

```

```
38         if negated(input_words[i - 1]) or negated(input_words[i
- 2]) or negated(input_words[i - 3]):
39             neg_count += 1
40             neg_words.append(input_words[i] + ' (with negation)'
)
41         else:
42             pos_count += 1
43             pos_words.append(input_words[i])
44     elif i == 2:
45         if negated(input_words[i - 1]) or negated(input_words[i
- 2]):
46             neg_count += 1
47             neg_words.append(input_words[i] + ' (with negation)'
)
48         else:
49             pos_count += 1
50             pos_words.append(input_words[i])
51     elif i == 1:
52         if negated(input_words[i - 1]):
53             neg_count += 1
54             neg_words.append(input_words[i] + ' (with negation)'
)
55         else:
56             pos_count += 1
57             pos_words.append(input_words[i])
58     elif i == 0:
59         pos_count += 1
60         pos_words.append(input_words[i])
61
62     #print('The results with negation check:', end='\n\n')
63     #print('The # of positive words:', pos_count)
64     #print('The # of negative words:', neg_count)
65     #print('The list of found positive words:', pos_words)
66     #print('The list of found negative words:', neg_words)
67     #print('\n', end='')
68     #print('Total word:', word_count)
69
70     results = [word_count, pos_count, neg_count, pos_words, neg_words]
71
72
73     return results
```

LISTING E.1: Python code for textual analysis

Loughran and McDonald Sentiment Word Lists

Some examples for **negative words**:

'abandon', 'abandoned', 'abandoning', 'abandonment', 'abandonments', 'abandons', 'abdicated', 'abdicates', 'abdication', 'abdicates', 'abdication', 'aberrant', 'aberration', 'aberrational', 'aberrations', 'abetting', 'abnormal', 'abnormalities', 'abnormality', 'abnormally', 'abolish', 'abolished', 'abolishes', 'abolishing', 'abrogate', 'abrogated', 'abrogates', 'abrogating', 'abrogation', 'abrogations', 'abrupt', 'abruptly', 'abruptness', 'absence', 'absences', 'absenteeism', 'abuse', 'abused', 'abuses', 'abusing', 'abusive', 'abusively', 'abusiveness', 'accident', 'accidental', 'accidentally', 'accidents', 'accusation', 'accusations', 'accuse', 'accused', 'accuses', 'accusing', 'acquiesce', 'acquiesced', 'acquiesces', 'acquiescing', 'acquit', 'acquits', 'acquittal', 'acquittals', 'acquitted', 'acquitting', 'adulterate', 'adulterated', 'adulterates', 'adulterating', 'adulteration', 'adulterations', 'adversarial', 'adversaries', 'adversary', 'adverse', 'adversely', 'adversities', 'adversity', 'aftermath', 'aftermaths', 'against', 'aggravate', 'aggravated', 'aggravates', 'aggravating', 'aggravation', 'aggravations', 'alerted', 'alerting', 'alienate', 'alienated', 'alienates', 'alienating', 'alienation', 'alienations', 'allegation', 'allegations', 'allege', 'alleged', 'allegedly', 'alleges', 'alleging', 'annoy', 'annoyance', 'annoyances', 'annoyed', 'annoying', 'annoys', 'annul', 'annulled', 'annulling', 'annulment', 'annulments', 'annuls', 'anomalies', 'anomalous', 'anomalously', 'anomaly', 'anticompetitive', 'antitrust', 'argue', 'argued', 'arguing', 'argument', 'argumentative', 'arguments', 'arrearage', 'arrears', 'arrest', 'arrested', 'arrests', 'artificially', 'assault', 'assaulted', 'assaulting', 'assaults', 'assertions', 'attrition', 'aversely', 'backdating', 'bad', 'bail', 'bailout', 'balk', 'balked', 'bankrupt', 'bankruptcies', 'bankruptcy', 'bankrupted', 'bankrupting', 'bankrupts', 'bans', 'barred', 'barrier', 'barriers', 'bottleneck', 'bottlenecks', 'boycott', 'boycotted', 'boycotting', 'boycotts', 'breach', 'breached', 'breaches', 'breaching', 'break', 'breakage', 'breakages', 'breakdown', 'breakdowns', 'breaking', 'breaks', 'bribe', 'bribed', 'briberies', 'bribery', 'bribes', 'bribing', 'bridge', 'broken', 'burden', 'burdened', 'burdening', 'burdens', 'burdensome', 'burned', 'calamities', 'calamitous', 'calamity', 'cancel', 'canceled', 'canceling', 'cancellation', 'cancellations', 'cancelled', 'cancelling', 'cancels', 'careless', 'carelessly', 'carelessness', 'catastrophe', 'catastrophes', 'catastrophic', 'catastrophically', 'caution', 'cautionary', 'cautioned', 'cautioning', 'cautions', 'cease', 'ceased', 'ceases', 'ceasing', 'censure', 'censured', 'censures', 'censuring', 'challenge', 'challenged', 'challenges', 'challenging', 'chargeoffs', 'circumvent', 'circumvented', 'circumventing', 'circumvention', 'circumventions', 'circumvents', 'claiming', 'claims', 'clawback', 'closed', 'closeout', 'closeouts', 'closing', 'closings', 'closure', 'closures', 'coerce', 'coerced', 'coerces', 'coercing', 'coercion', 'coercive', 'collapse', 'collapsed', 'collapses', 'collapsing', 'collision', 'collisions', 'collude', 'colluded', 'colludes', 'colluding', 'collusion', 'collusions', 'collusive', 'complains', 'complained', 'complaining', 'complains', 'complaint', 'complaints', 'complicate', 'complicated', 'complicates', 'complicating', 'complication', 'complications', 'compulsion', 'concealed', 'concealing', 'concede', 'conceded', 'concedes', 'conceding', 'concern', 'concerned', 'concerns', 'conciliating', 'conciliation', 'conciliations', 'condemn', 'condemnation', 'condemnations', 'condemned', 'condemning', 'condemns', 'condone', 'condoned', 'confess', 'confessed', 'confesses', 'confessing', 'confession', 'confine', 'confined', 'confinement', 'confinements', 'confines', 'confining', 'confiscate', 'confiscated', 'confiscates', 'confiscating', 'confiscation', 'confiscations', 'conflict', 'conflicted', 'conflicting', 'conflicts', 'confront', 'confrontation', 'confrontational', 'confrontations', 'confronted', 'confronting', 'confronts', 'confuse', 'confused', 'confuses', 'confusing', 'confusingly', 'confusion', 'conspiracies', 'conspiracy', 'conspirator', 'conspiratorial', 'conspirators', 'conspire', 'conspired', 'conspires', 'conspiring', 'contempt', 'contend', 'contended', 'contending', 'contends', 'contention', 'contentions', 'contentious', 'contentiously', 'contested', 'contesting', 'contraction', 'contractions', 'contradict', 'contradicted', 'contradicting', 'contradiction', 'contradictions', 'contradictory', 'contradicts', 'contrary', 'controversial', 'controversies', 'controversy', 'convict', 'convicted', 'convicting', 'conviction', 'convictions', 'corrected', 'correcting', 'correction', 'corrections', 'corrects', 'corrupt', 'corrupted', 'corrupting', 'corruption', 'corruptions', 'corruptly', 'corruptness', 'costly', 'counterclaim', 'counterclaimed', 'counterclaiming', 'counterclaims', 'counterfeit', 'counterfeited', 'counterfeiter', 'counterfeiters', 'counterfeiting', 'counterfeits', 'countermeasure', 'countermeasures', 'crime', 'crimes', 'criminal', 'criminally', 'criminals', 'crises', 'crisis', 'critical', 'critically', 'criticism', 'criticisms', 'criticize', 'criticized', 'criticizes', 'criticizing', 'crucial', 'crucially', 'culpability', 'culpable', 'culpably', 'cumbersome', 'curtail', 'curtailed', 'curtailing', 'curtailment', 'curtailments', 'curtails', 'cut', 'cutback', 'cutbacks', 'cyberattack', 'cyberattacks', 'cyberbullying', 'cybercrime', 'cybercrimes', 'cybercriminal', 'cybercriminals' (...)

Some examples for **positive words**:

'able', 'abundance', 'abundant', 'acclaimed', 'accomplish', 'accomplished', 'accomplishes', 'accomplishing', 'accomplishment', 'accomplishments', 'achieve', 'achieved', 'achievement', 'achievements', 'achieves', 'achieving', 'adequately', 'advancement', 'advancements', 'advances', 'advancing', 'advantage', 'advantaged', 'advantageous', 'advantageously', 'advantages', 'alliance', 'alliances', 'assure', 'assured', 'assures', 'assuring', 'attain', 'attained', 'attaining', 'attainment', 'attainments', 'attains', 'attractive', 'attractiveness', 'beautiful', 'beautifully', 'beneficial', 'beneficially', 'benefit', 'benefited', 'benefiting', 'benefitted', 'benefitting', 'best', 'better', 'bolstered', 'bolstering', 'bolsters', 'boom', 'booming', 'boost', 'boosted', 'breakthrough', 'breakthroughs', 'brilliant', 'charitable', 'collaborate', 'collaborated', 'collaborates', 'collaborating', 'collaboration', 'collaborations', 'collaborative', 'collaborator', 'collaborators', 'compliment', 'complimentary', 'complimented', 'complimenting', 'compliments', 'conclusive', 'conclusively', 'conductive', 'confident', 'constructive', 'constructively', 'courteous', 'creative', 'creatively', 'creativity', 'delight', 'delighted', 'delightful', 'delightfully', 'delighting', 'delights', 'dependability', 'dependable', 'desirable', 'desired', 'despite', 'destined', 'diligent', 'diligently', 'distinction', 'distinctions', 'distinctive', 'distinctively', 'distinctiveness', 'dream', 'easier', 'easily', 'easy', 'effective', 'efficiencies', 'efficiency', 'efficient', 'efficiently', 'empower', 'empowered', 'empowering', 'empowers', 'enable', 'enabled', 'enables', 'enabling', 'encouraged', 'encouragement', 'encourages', 'encouraging', 'enhance', 'enhanced', 'enhancement', 'enhancements', 'enhances', 'enhancing', 'enjoy', 'enjoyable', 'enjoyably', 'enjoyed', 'enjoying', 'enjoyment', 'enjoys', 'enthusiasm', 'enthusiastic', 'enthusiastically', 'excellence', 'excellent', 'excelling', 'excels', 'exceptional', 'exceptionally', 'excited', 'excitement', 'exciting', 'exclusive', 'exclusively', 'exclusiveness', 'exclusives', 'exclusivity', 'exemplary', 'fantastic', 'favorable', 'favorably', 'favored', 'favoring', 'favorite', 'favorites', 'friendly', 'gain', 'gained', 'gaining', 'gains', 'good', 'great', 'greater', 'greatest', 'greatly', 'greatness', 'happiest', 'happily', 'happiness', 'happy', 'highest', 'honor', 'honorable', 'honored', 'honoring', 'honors', 'ideal', 'impress', 'impressed', 'impresses', 'impressing', 'impressive', 'impressively', 'improve', 'improved', 'improvement', 'improvements', 'improves', 'improving', 'incredible', 'incredibly', 'influential', 'informative', 'ingenuity', 'innovate', 'innovated', 'innovates', 'innovating', 'innovation', 'innovations', 'innovative', 'innovativeness', 'innovator', 'innovators', 'insightful', 'inspiration', 'inspirational', 'integrity', 'invent', 'invented', 'inventing', 'invention', 'inventions', 'inventive', 'inventiveness', 'inventor', 'inventors', 'leadership', 'leading', 'loyal', 'lucrative', 'meritorious', 'opportunities', 'opportunity', 'optimistic', 'outperform', 'outperformed', 'outperforming', 'outperforms', 'perfect', 'perfected', 'perfectly', 'perfects', 'pleasant', 'pleasantly', 'pleased', 'pleasure', 'plentiful', 'popular', 'popularity', 'positive', 'positively', 'preeminence', 'preeminent', 'premier', 'premiere', 'prestige', 'prestigious', 'proactive', 'proactively', 'proficiency', 'proficient', 'proficiently', 'profitability', 'profitable', 'profitably', 'progress', 'progressed', 'progresses', 'progressing', 'prospered', 'prospering', 'prosperity', 'prosperous', 'prosperes', 'rebound', 'rebounded', 'rebounding', 'receptive', 'regain', 'regained', 'regaining', 'resolve', 'revolutionize', 'revolutionized', 'revolutionizes', 'revolutionizing', 'reward', 'rewarded', 'rewarding', 'rewards', 'satisfaction', 'satisfactorily', 'satisfactory', 'satisfied', 'satisfies', 'satisfy', 'satisfying', 'smooth', 'smoothing', 'smoothly', 'smooths', 'solves', 'solving', 'spectacular', 'spectacularly', 'stability', 'stabilization', 'stabilizations', 'stabilize', 'stabilized', 'stabilizes', 'stabilizing', 'stable', 'strength', 'strengthen', 'strengthened', 'strengthening', 'strengthens', 'strengths', 'strong', 'stronger', 'strongest', 'succeed', 'succeeded', 'succeeding', 'succeeds', 'success', 'successes', 'successful', 'successfully', 'superior', 'surpass', 'surpassed', 'surpasses', 'surpassing', 'transparency', 'tremendous', 'tremendously', 'unmatched', 'unparalleled', 'unsurpassed', 'upturn', 'upturns', 'valuable', 'versatile', 'versatility', 'vibrancy', 'vibrant', 'win', 'winner', 'winners', 'winning', 'worthy'

Are investors influenced by how earnings press releases are written?

(Henry, 2008)

Some examples for **negative words**:

'negative', 'negatives', 'fail', 'fails', 'failing', 'failure', 'weak', 'weakness', 'weaknesses', 'difficult', 'difficulty', 'hurdle', 'hurdles', 'obstacle', 'obstacles', 'slump', 'slumps', 'slumping', 'slumped', 'uncertain', 'uncertainty', 'unsettled', 'unfavorable', 'downturn', 'depressed', 'disappoint', 'disappoints', 'disappointing', 'disappointed', 'disappointment', 'risk', 'risks', 'risky', 'threat', 'threats', 'penalty', 'penalties', 'down', 'decrease', 'decreases', 'decreasing', 'decreased', 'decline', 'declines', 'declining', 'declined', 'fall', 'falls', 'falling', 'fell', 'fallen', 'drop', 'drops', 'dropping', 'dropped', 'deteriorate', 'deteriorates', 'deteriorating', 'deteriorated', 'worsen', 'worsens', 'worsening', 'weaken', 'weakens', 'weakening', 'weakened', 'worse', 'worst', 'low', 'lower', 'lowest', 'less', 'least', 'smaller', 'smallest', 'shrink', 'shrinks', 'shrinking', 'shrunk', 'below', 'under', 'challenge', 'challenges', 'challenging', 'challenged'

Some examples for **positive words**:

'positive', 'positives', 'success', 'successes', 'successful', 'succeed', 'succeeds', 'succeeding', 'succeeded', 'accomplish', 'accomplishes', 'accomplishing', 'accomplished', 'accomplishment', 'accomplishments', 'strong', 'strength', 'strengths', 'certain', 'certainty', 'definite', 'solid', 'excellent', 'good', 'leading', 'achieve', 'achieves', 'achieved', 'achieving', 'achievement', 'achievements', 'progress', 'progressing', 'deliver', 'delivers', 'delivered', 'delivering', 'leader', 'leading', 'pleased', 'reward', 'rewards', 'rewarding', 'rewarded', 'opportunity', 'opportunities', 'enjoy', 'enjoys', 'enjoying', 'enjoyed', 'encouraged', 'encouraging', 'up', 'increase', 'increases', 'increasing', 'increased', 'rise', 'rises', 'rising', 'rose', 'risen', 'improve', 'improves', 'improving', 'improved', 'improvement', 'improvements', 'strengthen', 'strengthens', 'strengthening', 'strengthened', 'stronger', 'strongest', 'better', 'best', 'more', 'most', 'above', 'record', 'high', 'higher', 'highest', 'greater', 'greatest', 'larger', 'largest', 'grow', 'grows', 'growing', 'grew', 'grown', 'growth', 'expand', 'expands', 'expanding', 'expanded', 'expansion', 'exceed', 'exceeds', 'exceeded', 'exceeding', 'beat', 'beats', 'beating'

Some examples for **negate words**:

"aint", "arent", "cannot", "cant", "couldnt", "darent", "didnt", "doesnt", "ain't", "aren't", "can't", "couldn't", "daren't", "didn't", "doesn't", "dont", "hadnt", "hasnt", "havent", "isnt", "mightnt", "mustnt", "neither", "don't", "hadn't", "hasn't", "haven't", "isn't", "mightn't", "mustn't", "neednt", "needn't", "never", "none", "nope", "nor", "not", "nothing", "nowhere", "oughtnt", "shant", "shouldnt", "wasnt", "werent", "oughtn't", "shan't", "shouldn't", "wasn't", "weren't", "without", "wont", "wouldnt", "won't", "wouldn't", "rarely", "seldom", "despite", "no", "nobody"

Bibliography

- Aalborg, Halvor Aarhus, Peter Molnár, and Jon Erik de Vries (2019). “What can explain the price, volatility and trading volume of Bitcoin?” In: *Finance Research Letters* 29, pp. 255–265.
- Aaron, Blake (2020). “How damnnng are Richard Burr’s and Kelly Loeffler’s coronavirus stock trades? Let’s break it down”. In: *Washington Post (Washington)*.
- Abdullah, Mohammad (2021). “The implication of machine learning for financial solvency prediction: an empirical analysis on public listed companies of Bangladesh”. In: *Journal of Asian Business and Economic Studies* ahead-of-print.ahead-of-print. ISSN: 2515-964X. DOI: [10.1108/JABES-11-2020-0128](https://doi.org/10.1108/JABES-11-2020-0128). URL: <https://doi.org/10.1108/JABES-11-2020-0128>.
- Abu-Ghunmi, Diana, Shaen Corbet, and Charles Larkin (2020). “An international analysis of the economic cost for countries located in crisis zones”. In: *Research in International Business and Finance* 51, p. 101090.
- Adda, Jérôme (2016). “Economic activity and the spread of viral diseases: Evidence from high frequency data”. In: *The Quarterly Journal of Economics* 131.2, pp. 891–941.
- Aggarwal, Raj, Aigbe Akhigbe, and Sunil K Mohanty (2012). “Oil price shocks and transportation firm asset prices”. In: *Energy Economics* 34.5, pp. 1370–1379.
- Ahn, Yongkil and Dongyeon Kim (2019). “Sentiment disagreement and bitcoin price fluctuations: a psycholinguistic approach”. In: *Applied Economics Letters*, pp. 1–5.
- Ajjoub, Carl, Thomas Walker, and Yunfei Zhao (2020). “Social media posts and stock returns: The Trump factor”. In: *International Journal of Managerial Finance*.
- Alexander, Carol and Michael Dakos (2020). “A critical investigation of cryptocurrency data and analysis”. In: *Quantitative Finance* 20.2, pp. 173–188.
- Ambros, Maximilian et al. (2020). “COVID-19 pandemic news and stock market reaction during the onset of the crisis: evidence from high-frequency data”. In: *Applied Economics Letters*, pp. 1–4.
- Ammer, John, Clara Vega, and Jon Wongswan (2010). “International transmission of US monetary policy shocks: Evidence from stock prices”. In: *Journal of Money, Credit and Banking* 42, pp. 179–198.
- Ante, Lennart (2021). “How Elon Musk’s Twitter Activity Moves Cryptocurrency Markets”. In: *Available at SSRN 3778844*.
- Arrow, Kenneth J (1959). “Functions of a theory of behavior under uncertainty”. In: *Metroeconomica* 11.1-2, pp. 12–20.

- Aysan Ahmet Faruk, Demir Ender Gozgor Giray and Chi Keung Marco Lau (2019). “Effects of the geopolitical risks on Bitcoin returns and volatility”. In: *Research in International Business and Finance* 47, pp. 511–518.
- Azar, Pablo D and Andrew W Lo (2016). “The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds”. In: *The Journal of Portfolio Management* 42.5, pp. 123–134.
- Baker, Scott R, Nicholas Bloom, and Steven J Davis (2016). “Measuring economic policy uncertainty”. In: *The quarterly journal of economics* 131.4, pp. 1593–1636.
- Baker, Scott R et al. (2020). “The unprecedented stock market reaction to COVID-19”. In: *The Review of Asset Pricing Studies*.
- Balcilar Mehmet, Bouri Elie Gupta Rangan and David Roubaud (2017). “Can volume predict Bitcoin returns and volatility? A quantiles-based approach”. In: *Economic Modelling* 64, pp. 74–81.
- Barberis, Nicholas and Richard Thaler (2003). “A survey of behavioral finance”. In: *Handbook of the Economics of Finance* 1, pp. 1053–1128.
- Barndorff-Nielsen, Ole E and Neil Shephard (2006). “Econometrics of testing for jumps in financial economics using bipower variation”. In: *Journal of financial Econometrics* 4.1, pp. 1–30.
- Barro, Robert J and Sanjay Misra (2016). “Gold returns”. In: *The Economic Journal* 126.594, pp. 1293–1317.
- Baruník, Jozef and Evžen Kocenda (2019). “Total, asymmetric and frequency connectedness between oil and forex markets”. In: *The Energy Journal* 40.Special Issue.
- Baruník, Jozef, Evžen Kočenda, and Lukáš Vácha (2016). “Asymmetric connectedness on the US stock market: Bad and good volatility spillovers”. In: *Journal of Financial Markets* 27, pp. 55–78.
- Baruník, Jozef and Tomáš Křehlík (2018). “Measuring the frequency dynamics of financial connectedness and systemic risk”. In: *Journal of Financial Econometrics* 16.2, pp. 271–296.
- Baur, Dirk G, Thomas Dimpfl, and Konstantin Kuck (2018). “Bitcoin, gold and the US dollar—A replication and extension”. In: *Finance Research Letters* 25, pp. 103–110.
- Baur, Dirk G and Thomas K McDermott (2010). “Is gold a safe haven? International evidence”. In: *Journal of Banking & Finance* 34.8, pp. 1886–1898.
- Beckers, Stan (2018). “Do Social Media Trump News? The Relative Importance of Social Media and News Based Sentiment for Market Timing”. In: *The Journal of Portfolio Management* 45.2, pp. 58–67.
- Benton, Allyson L and Andrew Q Philips (2018). “Does the@realDonaldTrump Really Matter to Financial Markets?” In: *American Journal of Political Science*.
- (2020). “Does the@realDonaldTrump really matter to financial markets?” In: *American Journal of Political Science* 64.1, pp. 169–190.
- Bernanke, Ben S (1983). “Irreversibility, uncertainty, and cyclical investment”. In: *The quarterly journal of economics* 98.1, pp. 85–106.

- Bernstein, Peter L (2012). *The power of gold: the history of an obsession*. John Wiley & Sons.
- Bhaskar, V, Robin Linacre, and Stephen Machin (2017). “The economic functioning of online drugs markets”. In: *Journal of Economic Behavior & Organization*.
- Bodnaruk, Andriy, Tim Loughran, and Bill McDonald (2015). “Using 10-K text to gauge financial constraints”. In: *Journal of Financial and Quantitative Analysis* 50.4, pp. 623–646.
- Boubaker, Heni and Syed Ali Raza (2017). “A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets”. In: *Energy Economics* 64, pp. 105–117.
- Bouoiyour, Jamal and Refk Selmi (2017). “The Bitcoin price formation: Beyond the fundamental sources”. In: *arXiv preprint arXiv:1707.01284*.
- Bouoiyour, Jamal, Refk Selmi, and Mark E Wohar (2018). “Measuring the response of gold prices to uncertainty: An analysis beyond the mean”. In: *Economic Modelling* 75, pp. 105–116.
- Bouri Elie, Azzi Georges and Anne Haubo Dyhrberg (2016). “On the return-volatility relationship in the Bitcoin market around the price crash of 2013”. In: *Available at SSRN 2869855*.
- Bouri Elie, Demirer Riza Gupta Rangan, Mark E Wohar, et al. (2019). “Gold, Platinum and the Predictability of Bond Risk Premia”. In:
- Bouri, Elie et al. (2017). “Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven?” In: *Applied Economics* 49.50, pp. 5063–5073.
- Bouri, Elie et al. (2020). “Gold, Platinum and the Predictability of Bond Risk Premia”. In: *Finance Research Letters*, p. 101490.
- Bouri Elie, Gupta Rangan, Amine Lahiani, and Muhammad Shahbaz (2018). “Testing for asymmetric nonlinear short-and long-run relationships between bitcoin, aggregate commodity and gold prices”. In: *Resources Policy* 57, pp. 224–235.
- Brauneis, Alexander and Roland Mestel (2018). “Price discovery of cryptocurrencies: Bitcoin and beyond”. In: *Economics Letters* 165, pp. 58–61.
- Bredin, Don et al. (2009). “European monetary policy surprises: the aggregate and sectoral stock market response”. In: *International Journal of Finance & Economics* 14.2, pp. 156–171.
- Brennan, Michael J (1976). “The supply of storage”. In: *The Economics of Futures Trading*. Springer, pp. 100–107.
- Briere, Marie, Kim Oosterlinck, and Ariane Szafarz (2015). “Virtual currency, tangible return: Portfolio diversification with bitcoin”. In: *Journal of Asset Management* 16.6, pp. 365–373.
- Broadstock, David C and Dayong Zhang (2019). “Social-media and intraday stock returns: The pricing power of sentiment”. In: *Finance Research Letters* 30, pp. 116–123.

- Burggraf, Tobias, Ralf Fendel, and Toan Luu Duc Huynh (2019). "Political news and stock prices: evidence from Trump's trade war". In: *Applied Economics Letters*, pp. 1–4.
- (2020). "Political news and stock prices: evidence from Trump's trade war". In: *Applied Economics Letters* 27.18, pp. 1485–1488.
- Burggraf, Tobias et al. (2019). "Do FEARS drive Bitcoin?" In: *Review of Behavioral Finance* 13.3, pp. 229–258.
- (2020). "Do FEARS drive Bitcoin?" In: *Review of Behavioral Finance*.
- Catania, Leopoldo, Stefano Grassi, and Francesco Ravazzolo (2019). "Forecasting cryptocurrencies under model and parameter instability". In: *International Journal of Forecasting* 35.2, pp. 485–501.
- Cheah, Eng-Tuck and John Fry (2015). "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin". In: *Economics Letters* 130, pp. 32–36.
- Chevapatrakul, Thanaset and Danilo V Mascia (2019). "Detecting overreaction in the Bitcoin market: A quantile autoregression approach". In: *Finance Research Letters* 30, pp. 371–377.
- Chibane, Messaoud and Nathalie Janson (2020). "Do Bitcoin Stylized Facts Depend on Geopolitical Risk?" In: *Available at SSRN 3530020*.
- Ciaian, Pavel, Miroslava Rajcaniova, and d'Artis Kancs (2016). "The economics of BitCoin price formation". In: *Applied Economics* 48.19, pp. 1799–1815.
- Cochrane, John H (2011). "Presidential address: Discount rates". In: *The Journal of finance* 66.4, pp. 1047–1108.
- Corbet, Shaen, Grace McHugh, and Andrew Meegan (2014). "The influence of central bank monetary policy announcements on cryptocurrency return volatility". In: *Investment management and financial innovations* 14, Iss. 4, pp. 60–72.
- Corbet, Shaen et al. (2018). "Exploring the dynamic relationships between cryptocurrencies and other financial assets". In: *Economics Letters* 165, pp. 28–34.
- Corbet, Shaen et al. (2020a). "Cryptocurrency reaction to fomic announcements: Evidence of heterogeneity based on blockchain stack position". In: *Journal of Financial Stability* 46, p. 100706.
- Corbet, Shaen et al. (2020b). "The impact of macroeconomic news on bitcoin returns". In: *The European Journal of Finance*, pp. 1–21.
- Cutler, David M, James M Poterba, and Lawrence H Summers (1989). "What moves the stock market". In: *Journal of Portfolio Management* 15.3, pp. 4–11.
- Da, Zhi, Joseph Engelberg, and Pengjie Gao (2011). "In search of attention". In: *The journal of finance* 66.5, pp. 1461–1499.
- Das, Debojyoti and M Kannadhasan (2018). "Do global factors impact bitcoin prices? Evidence from Wavelet approach". In: *Journal of Economic Research*.
- Das, Debojyoti et al. (2018). "Has co-movement dynamics in emerging stock markets changed after global financial crisis? New evidence from wavelet analysis". In: *Applied Economics Letters* 25.20, pp. 1447–1453.

- Demir, Ender et al. (2018). “Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation”. In: *Finance Research Letters* 26, pp. 145–149.
- Diebold, Francis X and Kamil Yilmaz (2009). “Measuring financial asset return and volatility spillovers, with application to global equity markets”. In: *The Economic Journal* 119.534, pp. 158–171.
- (2012). “Better to give than to receive: Predictive directional measurement of volatility spillovers”. In: *International Journal of Forecasting* 28.1, pp. 57–66.
- Donadelli, Michael and Luca Gerotto (2019). “Non-macro-based Google searches, uncertainty, and real economic activity”. In: *Research in International Business and Finance* 48, pp. 111–142.
- Dwyer, Gerald P (2015). “The economics of Bitcoin and similar private digital currencies”. In: *Journal of Financial Stability* 17, pp. 81–91.
- Dyhrberg, Anne Haubo (2016a). “Bitcoin, gold and the dollar—A GARCH volatility analysis”. In: *Finance Research Letters* 16, pp. 85–92.
- (2016b). “Hedging capabilities of bitcoin. Is it the virtual gold?” In: *Finance Research Letters* 16, pp. 139–144.
- Edmans, Alex, Diego Garcia, and Øyvind Norli (2007). “Sports sentiment and stock returns”. In: *The Journal of finance* 62.4, pp. 1967–1998.
- Elyasiani, Elyas, Iqbal Mansur, and Babatunde Odusami (2011). “Oil price shocks and industry stock returns”. In: *Energy Economics* 33.5, pp. 966–974.
- Engle, Robert F and Clive WJ Granger (1987). “Co-integration and error correction: representation, estimation, and testing”. In: *Econometrica: journal of the Econometric Society*, pp. 251–276.
- Eom, Cheoljun et al. (2019). “Bitcoin and investor sentiment: Statistical characteristics and predictability”. In: *Physica A: Statistical Mechanics and its Applications* 514, pp. 511–521.
- Erb, Claude B and Campbell R Harvey (2013). “The golden dilemma”. In: *Financial Analysts Journal* 69.4, pp. 10–42.
- Evans, Nigel and Sarah Elphick (2005). “Models of crisis management: An evaluation of their value for strategic planning in the international travel industry”. In: *International journal of tourism research* 7.3, pp. 135–150.
- Fama, Eugene F and Kenneth R French (1988). “Business cycles and the behavior of metals prices”. In: *The Journal of Finance* 43.5, pp. 1075–1093.
- (1996). “Multifactor explanations of asset pricing anomalies”. In: *The journal of finance* 51.1, pp. 55–84.
- (2015). “A five-factor asset pricing model”. In: *Journal of financial economics* 116.1, pp. 1–22.
- Fama, Eugene F and Merton H Miller (1972). *The theory of finance*. Holt Rinehart & Winston.
- Fan, Yi et al. (2019). “Bat coronaviruses in China”. In: *Viruses* 11.3, p. 210.

- Fang, Libing et al. (2019). “Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin?” In: *International Review of Financial Analysis* 61, pp. 29–36.
- Fernández-Macho, Javier (2012). “Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets”. In: *Physica A: Statistical Mechanics and its Applications* 391.4, pp. 1097–1104.
- Flori, Andrea (2019). “News and subjective beliefs: A Bayesian approach to Bitcoin investments”. In: *Research in International Business and Finance* 50, pp. 336–356.
- Foglia, Matteo and Peng-Fei Dai (2021b). ““Ubiquitous uncertainties”: spillovers across economic policy uncertainty and cryptocurrency uncertainty indices”. In: *Journal of Asian Business and Economic Studies* ahead-of-print.ahead-of-print. ISSN: 2515-964X. DOI: [10.1108/JABES-05-2021-0051](https://doi.org/10.1108/JABES-05-2021-0051). URL: <https://doi.org/10.1108/JABES-05-2021-0051>.
- (2021a). “Ubiquitous Uncertainties: Spillovers across Economic Policy Uncertainty and Cryptocurrency Uncertainty Indices”. In: *Journal of Asian Business and Economic Studies* forthcoming.
- Gabaix, Xavier, Arvind Krishnamurthy, and Olivier Vigneron (2007). “Limits of arbitrage: theory and evidence from the mortgage-backed securities market”. In: *The Journal of Finance* 62.2, pp. 557–595.
- Gao, Lili (2016). “Applications of MachLearning and Computational Linguistics in Financial Economics”. PhD thesis. Carnegie Mellon University.
- Gençay, Ramazan, Faruk Selçuk, and Brandon J Whitcher (2001). *An introduction to wavelets and other filtering methods in finance and economics*. Elsevier.
- Gomes, Joao F, Leonid Kogan, and Motohiro Yogo (2009). “Durability of output and expected stock returns”. In: *Journal of Political Economy* 117.5, pp. 941–986.
- Goodell, John W (2020). “COVID-19 and finance: Agendas for future research”. In: *Finance Research Letters*, p. 101512.
- Goodell, John W and Toan Luu Duc Huynh (2020). “Did Congress trade ahead? Considering the reaction of US industries to COVID-19”. In: *Finance Research Letters* 36, p. 101578.
- Gopinath, Gita (2020). “Limiting the economic fallout of the coronavirus with large targeted policies”. In: *Mitigating the COVID economic crisis: Act fast and do whatever it takes*, pp. 41–48.
- Granger, Clive WJ (1969). “Investigating causal relations by econometric models and cross-spectral methods”. In: *Econometrica: Journal of the Econometric Society*, pp. 424–438.
- Han, Xing, Xinfeng Ruan, and Yongxian Tan (2020). “Can the relative price ratio of gold to platinum predict the Chinese stock market?” In: *Pacific-Basin Finance Journal* 62, p. 101379.
- Harms, Philipp (2002). “Political risk and equity investment in developing countries”. In: *Applied Economics Letters* 9.6, pp. 377–380.

- Haroon, Omair and Syed Aun R Rizvi (2020). “COVID-19: Media coverage and financial markets behavior—A sectoral inquiry”. In: *Journal of Behavioral and Experimental Finance*, p. 100343.
- Henry, Elaine (2008). “Are investors influenced by how earnings press releases are written?” In: *The Journal of Business Communication (1973)* 45.4, pp. 363–407.
- Herbst, Anthony F and Craig W Slinkman (1984). “Political-economic cycles in the US stock market”. In: *Financial Analysts Journal* 40.2, pp. 38–44.
- Hkiri, Bisma et al. (2018). “The interconnections between US financial CDS spreads and control variables: New evidence using partial and multivariate wavelet coherences”. In: *International Review of Economics & Finance* 57, pp. 237–257.
- Hodrick, Robert J (1992). “Dividend yields and expected stock returns: Alternative procedures for inference and measurement”. In: *The Review of Financial Studies* 5.3, pp. 357–386.
- Huang, Darien and Mete Kilic (2019). “Gold, platinum, and expected stock returns”. In: *Journal of Financial Economics* 132.3, pp. 50–75.
- Hutto, Clayton and Eric Gilbert (2014). “Vader: A parsimonious rule-based model for sentiment analysis of social media text”. In: *Proceedings of the International AAAI Conference on Web and Social Media*. Vol. 8. 1.
- Huynh, Toan Luu Duc (2021). “Does Bitcoin React to Trump’s Tweets?” In: *Journal of Behavioral and Experimental Finance* 31, p. 100546.
- Huynh, Toan Luu Duc, Tobias Burggraf, and Mei Wang (2020). “Gold, platinum, and expected Bitcoin returns”. In: *Journal of Multinational Financial Management* 56, p. 100628.
- Huynh, Toan Luu Duc, Sang Phu Nguyen, and Duy Duong (2018). “Pricing assets with higher co-moments and value-at-risk by quantile regression approach: Evidence from Vietnam stock market”. In: *International Econometric Conference of Vietnam*. Springer, pp. 953–986.
- Huynh, Toan Luu Duc, Mei Wang, and Vinh Xuan Vo (2021). “Economic policy uncertainty and the Bitcoin market: An investigation in the COVID-19 pandemic with transfer entropy”. In: *The Singapore Economic Review*, pp. 1–27.
- Huynh, Toan Luu Duc et al. (2021). “Feverish sentiment and global equity market during COVID-19 Pandemic”. In: *Journal of Economic Behavior & Organization* forthcoming.
- Jiang, Yonghong, He Nie, and Weihua Ruan (2018). “Time-varying long-term memory in Bitcoin market”. In: *Finance Research Letters* 25, pp. 280–284.
- Kajtazi, Anton and Andrea Moro (2019). “The role of bitcoin in well diversified portfolios: A comparative global study”. In: *International Review of Financial Analysis* 61, pp. 143–157.
- Kaminski, Jermain (2014). “Nowcasting the bitcoin market with twitter signals”. In: *arXiv preprint arXiv:1406.7577*.

- Kang, Sang Hoon, Ron P McIver, and Jose Arreola Hernandez (2019). “Co-movements between Bitcoin and Gold: A wavelet coherence analysis”. In: *Physica A: Statistical Mechanics and its Applications*, p. 120888.
- Khuntia, Sashikanta and JK Pattanayak (2018). “Adaptive market hypothesis and evolving predictability of bitcoin”. In: *Economics Letters* 167, pp. 26–28.
- Kim, Neri et al. (2019). “Google searches and stock market activity: Evidence from Norway”. In: *Finance Research Letters* 28, pp. 208–220.
- Klaus, Jürgen and Christoph Koser (2020). “Measuring Trump: The Volfefe Index and its impact on European financial markets”. In: *Finance Research Letters*, p. 101447.
- Klein, Tony, Hien Pham Thu, and Thomas Walther (2018). “Bitcoin is not the New Gold—A comparison of volatility, correlation, and portfolio performance”. In: *International Review of Financial Analysis* 59, pp. 105–116.
- Koenker, Roger and Gilbert Bassett Jr (1978). “Regression quantiles”. In: *Econometrica: journal of the Econometric Society*, pp. 33–50.
- Koenker, Roger and Zhijie Xiao (2006). “Quantile autoregression”. In: *Journal of the American Statistical Association* 101.475, pp. 980–990.
- Koutmos, Dimitrios (2018a). “Bitcoin returns and transaction activity”. In: *Economics Letters* 167, pp. 81–85.
- (2018b). “Liquidity uncertainty and Bitcoin’s market microstructure”. In: *Economics Letters* 172, pp. 97–101.
- Kristoufek, Ladislav (2013). “BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era”. In: *Scientific reports* 3, p. 3415.
- (2015). “What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis”. In: *PLoS one* 10.4, e0123923.
- (2018). “On Bitcoin markets (in) efficiency and its evolution”. In: *Physica A: Statistical Mechanics and its Applications* 503, pp. 257–262.
- Liow, KimHiang et al. (2019). “Dynamic interdependence between the US and the securitized real estate markets of the Asian-Pacific economies”. In: *Journal of Property Investment & Finance* 37.1, pp. 92–117.
- Liu, Clare H (2017). “Applications of twitter emotion detection for stock market prediction”. PhD thesis. Massachusetts Institute of Technology.
- Liu, Shuming (2015). “Investor sentiment and stock market liquidity”. In: *Journal of Behavioral Finance* 16.1, pp. 51–67.
- Loughran, Tim and Bill McDonald (2011). “When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks”. In: *The Journal of Finance* 66.1, pp. 35–65.
- (2016). “Textual analysis in accounting and finance: A survey”. In: *Journal of Accounting Research* 54.4, pp. 1187–1230.
- Luther, William J and Josiah Olson (2013). “Bitcoin is memory”. In: *Journal of Prices & Markets* 3.3, p. 2015.
- Luther, William J and Alexander W Salter (2017). “Bitcoin and the bailout”. In: *The Quarterly Review of Economics and Finance* 66, pp. 50–56.

- MacKinlay, A Craig (1997). "Event studies in economics and finance". In: *Journal of economic literature* 35.1, pp. 13–39.
- Maggie, Sevens and O'Donnell Katy (2020). "House members, Senate aids traded stocks in early days of coronavirus". In: *Politico (2020)*.
- Mao, Haiou and Holger Görg (2020). "Friends like this: The impact of the US–China trade war on global value chains". In: *The World Economy* 43.7, pp. 1776–1791.
- Matkovskyy, Roman et al. (2019). "From bottom ten to top ten: the role of cryptocurrencies in enhancing portfolio return of poorly performing stocks". In: *Finance Research Letters*, p. 101405.
- Milgrom, Paul and Nancy Stokey (1982). "Information, trade and common knowledge". In: *Journal of economic theory* 26.1, pp. 17–27.
- Nadarajah, Saralees and Jeffrey Chu (2017). "On the inefficiency of Bitcoin". In: *Economics Letters* 150, pp. 6–9.
- Nandha, Mohan and Robert Faff (2008). "Does oil move equity prices? A global view". In: *Energy economics* 30.3, pp. 986–997.
- Nasir, Muhammad Ali et al. (2019). "Forecasting cryptocurrency returns and volume using search engines". In: *Financial Innovation* 5.1, p. 2.
- Newey, Whitney K and D Kenneth (1987). "A simple, positive semi-definite and autocorrelation consistent covariance matrix". In: *Econometrica* 55.3, p. 7.
- Omane-Adjepong, Maurice, Kofi Agyarko Ababio, and Paul Alagidede (2019). "Time-frequency analysis of behaviourally classified financial asset markets". In: *Research in International Business and Finance*.
- Omane-Adjepong, Maurice and Imhotep Paul Alagidede (2019). "Multiresolution analysis and spillovers of major cryptocurrency markets". In: *Research in International Business and Finance* 49, pp. 191–206.
- Ott, Brian L (2017). "The age of Twitter: Donald J. Trump and the politics of debase-ment". In: *Critical studies in media communication* 34.1, pp. 59–68.
- Pedersen, Thomas Q (2015). "Predictable return distributions". In: *Journal of Forecasting* 34.2, pp. 114–132.
- Percival, Donald B and Andrew T Walden (2000). *Wavelet methods for time series analysis*. Vol. 4. Cambridge university press.
- Philippas, Dionisis et al. (2019). "Media attention and Bitcoin prices". In: *Finance Research Letters* 30, pp. 37–43.
- Platanakis, Emmanouil and Andrew Urquhart (2019). "Should investors include bitcoin in their portfolios? a portfolio theory approach". In: *The British Accounting Review*, p. 100837.
- Popper, Nathaniel (2015). *Digital gold: The untold story of Bitcoin*. Penguin UK.
- Qi, Ming and Wenyao Wang (2013). "The monthly effects in Chinese gold market". In: *International Journal of Economics and Finance* 5.10, p141.
- Raimundo Júnior, Gerson De Souza et al. (2019). "Political risk, fear, and herding on the Brazilian stock exchange". In: *Applied Economics Letters*, pp. 1–5.

- Ramelli, Stefano and Alexander Wagner (2020). “What the stock market tells us about the consequences of COVID-19”. In: *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever* 63.
- Ranco Gabriele, Aleksovski Darko Caldarelli Guido Grčar Miha and Igor Mozetič (2015). “The effects of Twitter sentiment on stock price returns”. In: *PloS one* 10.9, e0138441.
- Reboredo, Juan C and Miguel A Rivera-Castro (2014). “Can gold hedge and preserve value when the US dollar depreciates?” In: *Economic Modelling* 39, pp. 168–173.
- Richard, Baldwin and Weder di Mauro Beatrice (2020). *Mitigating the COVID Economic Crisis. Act Fast and Do Whatever It Takes*. Centre for Economic Policy Research Press.
- Riley, William B and William A Luksetich (1980). “The market prefers republicans: Myth or reality”. In: *Journal of Financial and Quantitative Analysis* 15.3, pp. 541–560.
- Rufai, Sohaib R and Catey Bunce (2020). “World leaders’ usage of Twitter in response to the COVID-19 pandemic: a content analysis”. In: *Journal of Public Health* 42.3, pp. 510–516.
- Sakaki, Hamid (2019). “Oil price shocks and the equity market: Evidence for the S&P 500 sectoral indices”. In: *Research in International Business and Finance* 49, pp. 137–155.
- Salisu, Afees A, Kazeem Isah, and Lateef O Akanni (2019). “Improving the predictability of stock returns with Bitcoin prices”. In: *The North American Journal of Economics and Finance* 48, pp. 857–867.
- Schell, Daniel, Mei Wang, and Toan Luu Duc Huynh (2020). “This time is indeed different: A study on global market reactions to public health crisis”. In: *Journal of Behavioral and Experimental Finance*, p. 100349.
- Schwert, G William (1981). “Using financial data to measure effects of regulation”. In: *The Journal of Law and Economics* 24.1, pp. 121–158.
- Selmi, Refk, Aviral Kumar Tiwari, Shawkat Hammoudeh, et al. (2018). “Efficiency or speculation? A dynamic analysis of the Bitcoin market”. In: *Economics bulletin* 38.4, pp. 2037–2046.
- Selmi, Refk et al. (2018). “Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold”. In: *Energy Economics* 74, pp. 787–801.
- Shahzad, Syed Jawad Hussain et al. (2019a). “Is Bitcoin a better safe-haven investment than gold and commodities?” In: *International Review of Financial Analysis* 63, pp. 322–330.
- Shahzad, Syed Jawad Hussain et al. (2019b). “Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin”. In: *Economic Modelling*.
- Shen, Dehua, Andrew Urquhart, and Pengfei Wang (2019). “Does twitter predict Bitcoin?” In: *Economics Letters* 174, pp. 118–122.
- Street, Louise et al. (2016). “Gold Demand Trends”. In: *Technology* 3, p. 4.

- Swamy, Vighneswara, M Dharani, and Fumiko Takeda (2019). “Investor attention and Google Search Volume Index: Evidence from an emerging market using quantile regression analysis”. In: *Research in International Business and Finance* 50, pp. 1–17.
- Syed Zwick, Hélène and Sarfaraz Ali Shah Syed (2019). “Bitcoin and gold prices: A fledging long-term relationship”. In:
- Tetlock, Paul C (2007). “Giving content to investor sentiment: The role of media in the stock market”. In: *The Journal of finance* 62.3, pp. 1139–1168.
- Trucíos, Carlos (2019). “Forecasting Bitcoin risk measures: A robust approach”. In: *International Journal of Forecasting* 35.3, pp. 836–847.
- Tufano, Peter (1996). “Who manages risk? An empirical examination of risk management practices in the gold mining industry”. In: *the Journal of Finance* 51.4, pp. 1097–1137.
- Tweneboah, George and Paul Alagidede (2018). “Interdependence structure of precious metal prices: A multi-scale perspective”. In: *Resources Policy* 59, pp. 427–434.
- Urquhart, Andrew (2016). “The inefficiency of Bitcoin”. In: *Economics Letters* 148, pp. 80–82.
- (2018). “What causes the attention of Bitcoin?” In: *Economics Letters* 166, pp. 40–44.
- Vayanos, Dimitri and Jiang Wang (2012). “Liquidity and asset returns under asymmetric information and imperfect competition”. In: *The Review of Financial Studies* 25.5, pp. 1339–1365.
- Wagner, Alexander F, Richard J Zeckhauser, and Alexandre Ziegler (2018). “Company stock price reactions to the 2016 election shock: Trump, taxes, and trade”. In: *Journal of Financial Economics* 130.2, pp. 428–451.
- Wang, Gang-Jin et al. (2019). “When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin”. In: *Finance Research Letters* 31.
- Wang, Yudong, Chongfeng Wu, and Li Yang (2013). “Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries”. In: *Journal of Comparative economics* 41.4, pp. 1220–1239.
- Welch, Ivo and Amit Goyal (2007). “A comprehensive look at the empirical performance of equity premium prediction”. In: *The Review of Financial Studies* 21.4, pp. 1455–1508.
- Wolff, Dominik and Ulrich Neugebauer (2019). “Tree-based machine learning approaches for equity market predictions”. In: *Journal of Asset Management* 20.4, pp. 273–288.
- Wu, Fei (2019). “Sectoral contributions to systemic risk in the Chinese stock market”. In: *Finance Research Letters* 31.
- Xu, Caihong and Dong Zhang (2019). “Market openness and market quality in gold markets”. In: *Journal of Futures Markets* 39.3, pp. 384–401.

- Yang, Yung Chiang, Bohui Zhang, and Chu Zhang (2020). “Is information risk priced? Evidence from abnormal idiosyncratic volatility”. In: *Journal of Financial Economics* 135.2, pp. 528–554.
- Yarovaya, Larisa, Janusz Brzeszczyński, and Chi Keung Marco Lau (2016). “Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures”. In: *International Review of Financial Analysis* 43, pp. 96–114.
- You, Wanhai et al. (2017). “Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression”. In: *Energy Economics* 68, pp. 1–18.
- Yuneline, Mirza Hedismarlina (2019). “Analysis of cryptocurrency’s characteristics in four perspectives”. In: *Journal of Asian Business and Economic Studies*.
- Zavadska, Miroslava, Lucía Morales, and Joseph Coughlan (2020). “Brent crude oil prices volatility during major crises”. In: *Finance Research Letters* 32, p. 101078.
- Zhang, Dayong, Min Hu, and Qiang Ji (2020). “Financial markets under the global pandemic of COVID-19”. In: *Finance Research Letters*, p. 101528.
- Zhang, Xue, Hauke Fuehres, and Peter A Gloor (2011). “Predicting stock market indicators through twitter “I hope it is not as bad as I fear””. In: *Procedia-Social and Behavioral Sciences* 26, pp. 55–62.
- Zhu, Sheng, Jun Gao, and Meadhbh Sherman (2020). “The role of future economic conditions in the cross-section of stock returns: Evidence from the US and UK”. In: *Research in International Business and Finance* 52, p. 101193.