

AYLİN ASLAN

FINANCIAL ECONOMICS OF CRYPTOCURRENCY MARKETS

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FINANCIAL ECONOMICS OF CRYPTOCURRENCY MARKETS

A Ph.D. Dissertation

by

AYLİN ASLAN

Department of Management
İhsan Doğramacı Bilkent University
Ankara

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To my Family

FINANCIAL ECONOMICS OF CRYPTOCURRENCY MARKETS

The Graduate School of Economics and Social Sciences
of
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by

AYLİN ASLAN

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ABSTRACT

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Aslan, Aylin

Ph.D., Department of Management

Supervisor: Assist. Prof. Dr. Ahmet Şensoy

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The financial sector is currently experiencing a gradual change, driven by near-term digital and technological innovations. Emerging distributed ledger technologies (DLT), such as Blockchain, open new avenues for investors and companies providing fast, secure, and low-cost peer-to-peer transactions. Bitcoin, the first application of Blockchain, has inspired other applications and products, and led to the creation of thousands of other cryptocurrencies and new wave of crowdfunding. The primary purpose of this study is to investigate both cryptocurrencies and cryptocurrency-based crowdfunding. This dissertation made up of three main parts. In the first part, the determinants of Initial Coin Offering (ICO) success and aftermarket performance of ICOs are analyzed. We find that higher ratings, shorter duration, smaller share for token sale, larger number of experts and more members in the developing team have a positive impact on ICO success. We also observe a significant relationship between offer price, market sentiment and longer term post-ICO performance. Yet, key to a successful ICO and post-ICO performance differ between boom vs bust periods in the cryptocurrency markets. The second part deals with the weak-form efficiency property

of four largest cryptocurrencies by market capitalization, i.e. Bitcoin, Litecoin, Ripple and Ethereum. We use different Hurst exponent estimation techniques at different intraday frequencies. We reveal a U-shaped pattern for pricing efficiency with respect to the sampling frequency. The last part is about the hedge and safe-haven properties of Bitcoin, and its interlinkages to other precious metals (gold, silver, platinum, and palladium). Using high frequency data, we find evidence of spillover effects in volatility among Bitcoin and precious metals. Furthermore, the results suggest that the risk spillovers are time dependent and are sensitive to slowdowns in economic activity and political events. Overall, we contribute to the understanding of both market and corporate based approaches to the role of cryptocurrencies in capital markets.

Keywords: Asymmetric Volatility Connectedness, Cryptocurrencies, Efficient Market Hypothesis, High-frequency Trading, Initial Coin Offerings.

ÖZET

KRİPTO PARA PİYASALARININ FİNANSAL EKONOMİSİ

Aslan, Aylin

Doktora, İşletme

Tez Danışmanı: Dr. Öğr. Üyesi Ahmet Şensoy

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Finans sektörü son zamanlarda, kısa vadeli dijital ve teknolojik yeniliklerin etkisiyle kademeli bir değişim yaşamaktadır. Blokzinciri gibi gelişmekte olan dağıtık defter teknolojileri (DLT), yatırımcılar ve şirketler için hızlı, güvenli ve düşük maliyetli eşler arası işlemler sağlayan yeni fırsatlar sunmaktadır. Blokzincirin ilk uygulaması olan Bitcoin, diğer uygulamalara ve ürünlere ilham vermiş ve binlerce başka kripto para biriminin ve yeni kitle fonlaması dalgasının yaratılmasına yol açmıştır. Bu çalışmanın temel amacı hem kripto para birimlerini hem de kripto para birimi tabanlı kitle fonlamasını araştırmaktır. Bu tez üç ana bölümden oluşmaktadır. Birinci bölümde, ICO başarısının ve ICO'ların satış sonrası performansının belirleyicileri analiz edilmektedir. Daha yüksek derecelendirmelerin, daha kısa kampanya süresinin, token satışı için daha küçük payın, daha fazla sayıda uzman ve gelişen ekipte daha fazla üyenin ICO başarısı üzerinde olumlu bir etkisi olduğu görülmüştür. Ayrıca teklif fiyatı, piyasa duyarlılığı ve uzun vadeli ICO sonrası performans arasında önemli bir ilişki gözlemlemekteyiz. Ne var ki, başarılı bir ICO ve ICO sonrası performansın anahtarı, kripto para piyasalarındaki patlama ve düşüş dönemleri arasında farklılık göstermektedir. İkinci bölüm, Bitcoin, Litecoin, Ripple ve Ethereum gibi piyasa değerine göre en büyük dört

kripto para biriminin zayıf form etkinlik özelliğini incelemektedir. Farklı gün içi frekanslar için farklı Hurst üstel katsayı tahmin teknikleri kullanılmıştır. Fiyatlama etkinliği için örnekleme sıklığına göre U şeklinde bir model ortaya konmuştur. Son kısım, Bitcoin'in korunma ve güvenli liman özellikleri ve diğer kıymetli metallerle (altın, gümüş, platin ve paladyum) bağlantıları üzerinedir. Yüksek frekanslı verileri kullanarak, Bitcoin ve kıymetli metaller arasındaki dalgalanmada yayılma etkilerinin olduğu tespit edilmiştir. Ayrıca sonuçlar, risk yayılmalarının zamana bağlı olduğunu ve ekonomik faaliyetlerdeki yavaşlamalara ve siyasi olaylara duyarlı olduğunu göstermektedir. Genel olarak, kripto para birimlerinin sermaye piyasalarındaki rolüne hem piyasa hem de kurumsal tabanlı yaklaşımların anlaşılmasına katkıda bulunulmuştur.

Anahtar Kelimeler: Asimetrik Volatilite Yayılımı, Etkin Piyasa Hipotezi, İlk Kripto Para Arzı, Kripto Para, Yüksek Frekanslı İşlemler

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CHAPTER I

INTRODUCTION

1.1. Overview

The world of finance is currently undergoing a striking transformation, motivated by rapid advances in digital technology. Blockchain based distributed ledger technology is the backbone of the digital revolution which was the underlying technology behind the cryptocurrency Bitcoin introduced in 2009. It was the first widespread use of Blockchain technology. Since then, the trend towards digitalization has gained momentum bringing about the promotion of new types of financial products as well as new process and platforms. Initial coin offerings are one of the most common implementations of Blockchain for finance, allowing entrepreneurial ventures an alternative way of raising funds to develop a new project or product.

This thesis consists of three main parts centering on cryptocurrencies and tokens. We aim to contribute to emerging literature on both entrepreneurial finance in regard to ICOs and asset pricing of cryptocurrencies.

In Chapter 2, we study the market for initial coin offerings (ICO). A comprehensive analysis is conducted on the determinants of the amount raised in ICOs using hand-compiled data. Our evidence suggests that ICOs with higher ratings, larger number of experts and more members in developing team have a greater likelihood of success and raising more funds. In addition, having shorter planned token sale duration, retaining larger fraction of tokens, not offering bonus for early investors and not setting higher hardcap levels have a positive impact on the success of the campaign. Additionally, two common phenomena for initial public offerings (i.e. underpricing and post-IPO performance) are evaluated in the ICO context. Empirical analysis

shows that offer price, market sentiment, raised and ICO duration are significant drivers of underpricing. Moreover, market sentiment measured with CCI30 index, the offer price, the end-to-open return and the first listing day return play a major role in explaining longer-term post-ICO performance. We also focus on the determinants of ICO success and aftermarket performance of ICOs during both the market boom and crash. The results suggest that the key success ICO factors and ICO returns differ between boom and bust periods.

In Chapter 3, we investigate the nexus between weak-form efficiency and intraday sampling frequency for the highest capitalized cryptocurrencies. Applying a battery of long memory tests, we provide evidence of major discrepancies on the predictability of cryptocurrency returns for alternative high frequency intervals. Accordingly, efficiency demonstrates a U-shaped pattern with respect to alternative sampling frequencies, hence there exists an optimal intraday sampling frequency that maximizes the market efficiency. These findings have important implications for portfolio analysis, risk management, regulations and administrative rulings in the cryptocurrency markets.

In Chapter 4, we examine the asymmetric volatility connectedness between Bitcoin and major precious metals markets (gold, silver, palladium, and platinum). We use high-frequency data with methodologies introduced by Diebold and Yilmaz (2014) and Baruník et al. (2017). The results show evidence of significant volatility spillover effects between Bitcoin and precious metals. Moreover, the risk spillovers vary over time and are sensitive to slowdowns in economic activity and political events (e.g., the Brexit vote and the US presidential election). Palladium is the largest net contributor of spillovers while Bitcoin is a net recipient. Finally, evidence of asymmetry in semi-volatility transmission shows that Bitcoin heavily transmits net-positive spillovers to other assets. The results of our research are of interest and importance to investors, portfolio managers, and policy-makers, as the results can readily inform their decision-making.

CHAPTER II

DETERMINANTS OF ICO SUCCESS AND POST-ICO PERFORMANCE

2.1. Introduction

In recent years, initial coin offerings (ICOs) have emerged as a new form of crowdfunding in the world of cryptocurrencies with the potential of replacing conventional financing sources. ICOs combine crowdfunding or equity crowdfunding aspects with distributed ledger technology and they provide for entrepreneurial ventures an alternative route to raise external finance by issuing and selling tokens to a crowd of investors (Fish, 2019). Tokens¹ are blockchain-powered digital assets for which all transaction records are secured through encryption techniques. Additionally, no intermediation is needed to conduct an ICO thanks to innovative technology enabled using smart contract, suggesting low transaction fees.

As the name infers, an ICO is a close analogue to a corporate initial public offering (IPO) of equity shares. Instead of offering the company shares for the public to purchase, digital coins or tokens are distributed. Except for selling a different asset, these two funding methods through public offering have some other substantial differences: IPOs are pursued by already established business whereas ICOs has been

¹ There are two main categories of ICO tokens: security tokens and utility tokens. Security tokens grant to holders certain ownership rights of a company, while utility tokens represent future access to the services or products provided by the issuers. Neatly fitting digital tokens into one of the above types matters since tokens that are deemed securities should be issued in compliance with the SEC's rules and regulations. Utility tokens are typically exempted from federal laws. To figure out if a token is a security, the SEC uses the Howey test which is a test created by the Supreme Court for determining whether certain transaction involves an investment contracts. A crypto token that passes the Howey Test is considered as a security token (<https://www.sec.gov/corpfin/framework-investment-contract-analysis-digital-assets>).

avored by new business ventures. In the context of an IPO, underwriters, serving as an intermediary between investors and issuing companies, determine IPO prices. Unlike IPOs, underwriters do not set companies' offer prices in ICOs. Prior to raising funds via IPOs, companies face regulatory hurdles or disclosure obligations. ICOs, by contrast, have gained popularity owing to their unregulated nature and close to zero transaction cost. Therefore, ICOs are usually performed by young startups in the tech industry to work around the regulatory requirements and costly intermediaries (such as exchanges, brokerages, underwriters, etc.). Taken together, ICOs potentially have different key success factors as well as different underpricing and post-offering performance pattern from IPOs.

Previous literature compares ICOs to conventional forms of corporate finance (Momtaz and Rennertseder, 2018; Ofir and Sadeh, 2019) and explores the determinants of ICO funding success (e.g. Adhami et al., 2018; Amsden and Schweizer, 2018; Fish, 2019; Bourvea et al., 2018, Lee et al., 2019, De Jong et al., 2018), inter alia, the dynamics of ICO token returns in the short and long run (e.g. Benedetti and Kostovestky, 2018; Lyandres et al., 2019; Momtaz, 2018a; Momtaz, 2018b; Felix and von Eije, 2019). We supplement the existing research by investigating the success of an ICO success with a comprehensive set of variables. We then link our empirical results to the IPO and crowdfunding literatures and provide theoretical explanations for our findings in the ICO domain.

In line with literature, we find that higher expert rating, lower fraction of distributed tokens, shorter token sale duration, not having bonus scheme increase the chances of success. Additionally, we go further beyond fundraising success and evaluate two common phenomena for initial public offerings (i.e. underpricing and post-IPO performance) in the ICO context. The results confirm previous research and demonstrate that there is underpricing in ICOs, with an average return of 261% from the ICO price to the first day's closing price. As expected, the average underpricing in ICOs is considerable higher in comparison to IPOs since ICO companies are at the very early stages of development and face uncertain future demand on their non-existent product. The regression analysis show that ICO offer price, market sentiment measured by the CCI30 cryptocurrency market index, funds raised and duration of ICO campaign are significant drivers of underpricing. Furthermore, we find that

market sentiment, the offer price, the end-to-open return and the first listing day return are significant determinants of ICO returns at all horizons.

In our research, we also contribute to the literature by discovering the ICO market characteristics and determinants of ICO success during different phases. Although previous studies have examined many different aspects of ICOs such as the geography of ICOs (Huang et al., 2018), liquidity and trading volume in the ICO market (Howell et al., 2018), specific success factors resulting from asymmetric information such as CEO loyalty (Momtaz, 2018c) and emotions (Momtaz, 2018d) as well as moral hazard (Momtaz 2018e), investor sentiment on the ICO market (Drobetz et al., 2019) and contribute to theory (Cong et al., 2018, Sockin and Xiong (2018), Li and Mann (2018), Catalini and Gans (2018) and Chod and Lyandres (2018), they usually ignore to distinguish between bearish vs. bullish cryptocurrency market periods. One aim of this paper is to fill this gap in the current literature. Therefore, we review and synthesize past research to identify critical variables that may potentially explain fundraising success and returns to investing in ICOs attempting between April 2015 and January 2020. This period offers additional insight because it encompasses three distinct subperiods: bullish for both cryptocurrency and ICO markets, bullish for ICO market but bearish subperiods for cryptocurrency market, and bearish subperiods for both cryptocurrency and ICO markets. As such, we divide our sample into three subsamples in order to account for differences induced by the process of development undergone by cryptocurrency and ICO market.

We address the following areas to afford a new insight into the ICOs regarding different market trends: potential determinants of the ICO success and post-listing returns and longer-term returns for ICO tokens. The empirical results suggest that investors make their decisions whether to invest in ICO according to “rating” in bullish periods of ICO market. However, they substitute it with “number of experts” during the bearish period. In addition, we find evidence that market sentiment and first day return remain significant drivers of ICO short and long-term returns over subperiods, while the impact of campaign or company characteristics tend to vary across different market trends.

The remainder of this paper is organized as follows. Section 2 provides literature review, Section 3 introduces the sample data, Section 4 presents empirical results and discusses their implications, and Section 5 concludes.

2.2. Literature Review

On the theoretical side, several papers are concerned with identifying how ICOs could be beneficial for entrepreneurs. Cong et al. (2018) develop dynamic asset valuation model of cryptocurrencies and tokens on blockchain-based platforms and show the roles of the tokens in accelerating user adoption. Sockin and Xiong (2018) model a cryptocurrency as membership to a digital platform developed to facilitate decentralized transactions of certain goods or services among users, whereas Li and Mann (2018) present a model to explain how tokens and ICOs create value in the presence of a network effect, by solving coordination failure during platform building. Catalini and Gans (2018) show that ICO allows an entrepreneur to extract information about consumers' willingness to pay, providing ventures with higher returns compared to equity finance. Similarly, Chod and Lyandres (2019) present an agency theory and elaborate the reasons for why ICOs can have an advantage over traditional venture capital financing.

On the empirical side, initial works explore success factors behind ICOs. Adhami et al. (2018) examine 253 ICO campaigns and find that probability of an ICO's success in terms of amount raised depends on various factors such as the publicly available code source of the ICO, the presale of tokens, and the right to access a specific service or share profits. Amsden & Schweizer (2018) consider coin tradability as the primary ICO success measure, and stated that venture uncertainty (shorter whitepapers, not being on social media channels such as Github and Telegram, higher percentage of tokens distributed) has a negative influence, whereas venture quality (better connected CEOs and larger team size) has a positive influence, on ICO success. The importance of the existence of a white paper or disclosure of specific information for ICO success is confirmed by Howell et al. (2018), who document that liquidity and trading volume of exchange-traded tokens are higher when issuers disclose more information. According to the Fisch's (2019) signaling-related

evidence, the amount raised in an ICO is determined by high quality source codes, technical white papers, higher token supply, and having an Ethereum-based token.

De Jong et al. (2018) find evidence that higher rating by cryptocurrency experts, organizing a presale, offering bonus schemes, and having shorter token sale durations positively predict ICO success. In a similar vein, Lee et al. (2019) test the wisdom-of-crowds hypothesis using the analyst rating as a proxy. The authors suggest that analysts' ratings serving as substitutes for traditional underwriters' intermediary roles have positively correlated with ICO success. The importance of ICO rating providers on reducing information asymmetry, and hence enhancing ICO success and post-ICO performance is also highlighted by Bourveau et al. (2018). Further, De Jong et al. (2018) highlight the positive influence of a larger project team on the amount raised, although Fisch (2019) finds that it has no effect. Lyandres et al. (2019) report that the success of an ICO is positively associated with the presence of whitelist or/and KYC requirements. However, this finding is challenged with Lee et al. (2019), who find KYC indicator to be insignificant and negative.

Following the research on the characteristics of successful fundraising campaigns, empirical literature proceeds by examining ICO returns in the short run and long run. Several studies analyze the determinants of ICO underpricing (Benedetti and Kostovetsky, 2018; Momtaz, 2018b; Lyandres et al., 2019; Felix and von Eije, 2019). While Momtaz (2018b) shows on average positive returns on the first day of trading, Benedetti and Kostovetsky (2018) document positive returns to investing at listing and over two months after the listing date and relate the performance to Twitter followers and activity. In line with IPO underpricing literature, Felix and von Eije (2019) and Lyandres et al (2019) find the evidence of negative relation between issue size and underpricing of ICO, supporting the notion that larger issue reduces information asymmetry. Drobetz et al. (2019) identify investor sentiment and returns on the first day of trading as being influencing factors for long term ICO returns. Hu et al. (2018) examine returns of over 200 cryptocurrencies and find that they are all highly correlated with Bitcoin returns.

2.3. Data and Variables

2.3.1. Data

The sample used in this research is compiled from different ICO aggregator websites, as there is no standard and universal data source for ICOs. First, the initial dataset is built on the icobench.com, which is the most comprehensive database of ICO data. From this database, we gather the following information for 5579 ICOs from April 2015 to January 2020 by building a scraper in the programming language Python: startup name, token ticker, country of registration, rating, number of experts, start and end dates of an ICO, soft and hard caps, capital raised, types of currencies accepted for an ICO, token price, the percent of tokens for sale, the industry categories the ICO addresses, whether the ICO offers bonus, whether the ICO conducts a presale, whether the project uses a KYC processor a whitelist, whether citizens from certain countries are excluded from the ICO². Second, we supplement the data with information from icodrops.com, tokendata.io, icodata.io, icorating.com and icomarks.com by hand, if the data acquired from icobench.com is missing. Furthermore, upon manual checks, the data is verified with the information retrieved from abovementioned websites. Although icobench.com has the highest number of observations, it provides low quality data for certain variables. Therefore, in case of disagreement in variable values of icobench.com and other data sources used in this study, we use the latter. Due to the incomplete information on raised amount, start and end date, the final data set consists of 2318 ICOs. Third, we include the CCI30 index as obtained from cci30.com at the start of the ICO using the daily opening values. The CCI30 index tracks the top 30 cryptocurrencies by market capitalization, serving as a proxy for market sentiment. Lastly, 2318 ICOs is linked to daily cryptocurrency trading records on coinmarketcap.com, which is the leading source of cryptocurrency price and volume data used mostly in the academic literature. Matching on token name string, ticker symbols and official website URL yields 802 ICOs with secondary market price data.

² Gross proceed, hard cap, soft cap and token price are mostly quoted in fiat currencies such as dollar and euro or cryptocurrencies such as ETH and BTC. We convert all entries to dollar as of last day of ICO campaign.

Figure 2.1 illustrates the evolution of ICOs quarterly. The first ICO was held by Mastercoin (now called Omni) in July 2013. The project was able to raise around 5,000 Bitcoin, an amount worth around \$500,000. Since then, the success of this fundraising campaign inspired other projects and thousands of companies leaped into and deployed the ICO model to fund their product development efforts. As depicted in Figure 2.1, the ICO mania exploded between mid-2017 and early 2018. Yet for all the growth around these token sales, the rise of failed projects and scams are the troubling results. Accordingly, China and South Korea had both banned initial coin offerings in the third quarter of 2017 due to concerns over the potential for financial scams. Greater regulatory scrutiny around the world led many issuing entities move to jurisdictions with lighter-touch regulation such as the Cayman Islands and the Virgin Islands. Token sale rally continued two years until the market sentiment started to alter in 2018. As investors became more prudent and regulators started to be more stringent, the bull market turns a bear market in the third quarter of 2018.

[Insert Figure 2.1 about here.]

2.3.2. Variables

2.3.2.1. Dependent Variables

For this study, we have four different dependent variables:

-Gross Proceed

First dependent variable is the amount of funding raised in ICO campaigns. This is a broadly used dependent variable in entrepreneurial finance research as a measure of ICO success. Since the distribution of the variable is highly skewed, we use natural logarithm of gross proceeds, in line with prior research. We further exploit this data with second dependent variable.

-Success/Fail

Our second dependent variable is a binary variable denoting ICO success that takes the value 1, if the ICO hits its softcap (if any) or the amount of money raised is more than \$0.5 million in the absence of a soft cap and zero otherwise (with reference to the idea by Mironov and Campbell, 2018; Lee et al., 2019). To decide on the status, information about raised amount of ventures is needed. Unfortunately, we obtain data on raised amount only for 2318 of the ventures, 1706 of which complete the campaign successfully. We have information on amount raised only for 612 failed ICOs, since icobench.com deletes failed ICOs from their database, as do many other data aggregators.

-Underpricing

Underpricing is the phenomenon whereby the offer price is on average set below its real value. This phenomenon has been subject to many studies in the context of IPOs, suggesting many theories to explain possible reasons for IPO underpricing. Most of the research is based on the information asymmetry theory. Although there are important distinctions, the ICO process is somewhat similar to an IPO and hence it is useful to explore underpricing phenomenon surrounding ICOs by consulting the IPO literature. Underpricing equals $P_1/P_{ICO} - 1$, where P_1 and P_{ICO} are first listing day closing price and ICO offer price, respectively.

-Post-ICO Performance

First-day return is measured from the first trading day opening price to first trading day closing price. Similarly, ***one-week, one-month, three-month, six-month, and one-year returns*** are measured from the first trading day closing price to the 7th, 30th, 90th, 180th and 365th trading closing prices, respectively.

In our analysis, we test several characteristics of the ICO process that may influence its success and post-performance, and the details of these characteristics are provided below:

2.3.2.2. Independent Variables

-Softcap

Similar to the classic crowdfunding, a venture might decide on setting up a softcap, which is a minimum amount to be raised. If this amount is not hit, the project is not launched, and funds are usually returned to investors.

-Hardcap

The venture may also set a hardcap, which is the maximum amount that can be raised by the project. It is a rare that no hardcap is provided since it is important for potential investors to see the clear and concise fundraising goal of the startup. Therefore, the team should look at their roadmap and specify the maximum amount that they need for their product.

-Duration of offering

‘Duration of offering’ announced by the project team as an active period when the ICO is launched is adopted as a variable to determine the effects of the length of the campaign. The variable is defined in days between the ICO start and the end date.

-ERC20

Ethereum is the prominent platform for conducting ICOs. The Ethereum standard (ERC20) provides a set of rules for transfer tokens, as well as enables interacting applications such as wallets and crypto exchanges. Investors may recognize ICOs using Ethereum’s infrastructure safer than other token exchange platform. Therefore, we include a dummy variable equal to 1 if ICOs build on ERC20 Blockchain and 0 if the project uses its own or other technology.

-Rating

Icobench.com provides experts’ rating ranging business ventures from zero to five, zero being the lowest and five being the highest quality of ICO. There are four criteria

employed in the ratings: profile, team, vision, and product. We use the weighted average rating of the experts, which may serve as a tool for mitigating asymmetric information problem during the process.

-Expert

In this paper, we explore how the “wisdom of crowds,” the collective action of a group of individuals rather than advice from a single expert, helps mitigate information asymmetry associated with an ICO.

-Bonus

The variable Bonus is a dummy variable equal to 1 if a bonus is offered to early investors, 0 otherwise.

-KYC/Whitelist

Know your customer (KYC) policy makes the potential investors provide some information such as their addresses, citizenship, and photo IDs to verify their identity. Whitelist, on the other hand, requires registration for participation. Thanks to these procedures, illegal activities of investors most interested in the guise of anonymity can be prevented. However, it may also discourage potential investors who do not want to share their personal data due to cyber security threats. Empirical analysis revealed contradictory results on the effect of the implementation of a KYC process or a whitelist on the success and aftermarket performance of ICOs. Exploring combined effect, we include a dummy variable which has the value of 1 if the project implemented a KYC process and/or a whitelist during the ICO and 0 otherwise.

-Presale

The variable Presale is a dummy variable which equal to 1 if a presale is carried out before the main crowdsale and equal to 0 if otherwise.

- # Industry Category

Companies choose among 29 industry categories determined by icobench.com which shows the future sphere of activity. The number of categories the ICO falls into is a

measure for diversification. High number of industries is an indicator of the broader areas of future usage of a company's products.

-Team Members

Another variable that was employed in the study is the number of team members. A large team creates trust in the investors believing that there will be enough people to carry out the project. As the number of contacts increase, there will be more contribution to the project's future endeavors.

-Distributed in ICO

The next variable that we use in the analysis is the ratio of the tokens offered in sales to the total supply of tokens. This ratio is indicative of how successful the ICO will be in terms of the trust it creates in the market. The more tokens a venture retains ownership share the more quality it signals.

-US Restriction

Since SEC started audit the freewheeling operations of ICOs, several ventures do not admit investors from US from participating in the token sale to escape the constraints of regulation. A dummy variable that equals to 1 if ICOs do not accept US based investors and 0 if otherwise.

-Accepted Fiat

A dummy variable that equals to 1 if investors could buy tokens with fiat currencies (Dollar, Euro, Yuan, and other government-issued currencies) and 0 if otherwise.

-Major cryptocurrencies

A dummy variable that equals to 1 if investors could buy tokens only with four major cryptocurrencies, i.e., Bitcoin, Ethereum, Litecoin and Ripple.

-CCI30 Index

The market cap weighted index of the 30 largest cryptocurrencies is used as a benchmark for cryptocurrencies and Blockchain sector to measure the overall market movements.

2.4. Empirical Results

2.4.1. Descriptive Statistics

Table 2.1 displays descriptive statistics for the subsample of ventures with amount raised data (N=2318) and the subsample of ventures with the price data (N=802). The first column shows the variables included in the analysis. The second column shows the number of observation available for the ICO. The next three columns display the mean, median, and standard deviation. The last two columns show the minimum value and the maximum values of the variable.

The mean rating of the sample is 3.13, provided by icobench.com ranging from 0 (weak) to 5 (strong). The ERC-20 standard is used by 75% of the project in our sample, highlighting that it is dominant platform for ICOs. The average ICO duration is 52 days, varying between 1 and 760. The offer price varies from \$0.0000204 to \$7554.6 per token. Furthermore, the industry categories that a venture could select on icobench.com is between 1 and 29; the data shows that the minimum is 1 and the maximum 12 in this sample. 2318 ventures in our sample raised a total funding of \$14.3 million. The average ICO team member is 10, which is in line related ICO studies (De Jong et al., 2018; Fish and Momtaz, 2020). The proportion of tokens distributed to the public in an ICO is on average 51.3%. Less than half of all sample firms sets KYC process. Regarding promotional tools, less than half of the ICOs offers bonus and only one quarter of the ICO ventures conduct presale. The mean of CCI30 index (in thousand) at the start day of the ICOs in the sample is 6.2. However, it is noteworthy that the index ranged from 0.088 to 20.8, suggesting significant variation. The mean ICO underpricing during our sample period is 261%. These findings are reminiscent of those reported in related studies on underpricing of ICOs (e.g., Lee et al. (2018), Lyandres et al. (2018), Benedetti and Kostovetsky (2018)).

The mean (median) returns for 7,30, 90, 180, and 365 days after the first listing day are on positive (negative), consistent with the evidence of long-return post-ICO performance (Lee et al. (2018) and Lyandres et al. (2018)). These results suggest that mean long-term returns are attributed to a small number of ICOs with extremely high returns.

[Insert Table 2.1 about here.]

2.4.2. Empirical Analysis

The empirical analysis starts with testing determinants of ICO success: hitting its softcap (if any) or the amount of money raised which is more than \$0.5 million in the absence of a soft cap and raising more funds. We further focus on the subsamples of ICOs whether things become considerably different during various market conditions. Then, we test the existence of ICO underpricing with the proxies of IPO literature. We proceed by querying ICO returns at different horizons: first day of trading and longer-term returns. Finally, we analyze the returns to investors through ICO in different phases with same set of variables.

2.4.2.1. ICO Success

The first part of our analysis examines the relation between the attributes of ICO and success measures. Column 1 in Table 2.2 reports the results of logistic regressions, where the dependent variable is ‘Success’, a binary variable being 1 if the ICO campaign has been successful and being 0 if the conditions previously specified are not satisfied.

First column presents the logit coefficients and their standard errors with country and quarter fixed effects. To facilitate sensible interpretation of the models, in the second columns of all logistic regressions here, we report the marginal effects associated with each explanatory variable. We estimate the regression using the entire sample of ICOs for which we have required data. Our results show that the probability of

success is increasing in expert rating, which indicates that information intermediaries serve as a tool for mitigating asymmetric information, which is consistent with the Spence's (1973) signaling theory. The number of experts providing ratings for an ICO also positively related to fundraising success, in line with the 'wisdom of the crowd' notion in which investors of the crypto market view the opinions of large groups of people credible in investment decision and due diligence process. From the company characters, having a larger project team shows positive signs for fundraising success, which acts as an indicator of team quality.

We also find evidence that ICO campaign characteristics have signaling roles on the fundraising success. The percentage of tokens distributed in ICO is positively associated to fundraising success, suggesting that investors favor ICOs in which smaller portions of the companies are sold. This result is also consistent with Leland and Pyle (1977) (in the context of IPOs) and Vismara (2016) (in the context of crowdfunding), suggesting that potential investors are less likely to invest in if the company offers more of its shares to the public. As long as the venture shows more ownership in the project by retaining its shares to itself, to put it in another way by having more skin in the game, there is a positive impact on both success and return of ICO.

The results show the evidence that having a shorter planned token sale duration leads to higher probability of ICO success. Being in line with the crowdfunding literature, the longer it takes to issue tokens the less probable it is for the venture to succeed. Drawing on reward-based crowdfunding literature, Mollick (2014) refers to duration of offerings as an important indicator for the realization of the fund-raising goals of the entrepreneurs. He argues that investors may not feel safe to invest in the ICO since a longer period signals lack of confidence on the part of venture. On the other hand, having a bonus scheme and the target amount for the hardcap decrease the success likelihood. A possible reason is that potential investors often refrain from investing in worthwhile initiatives for fear of falling foul of scams and fraudsters.

The softcap has significantly negative effect on the likelihood of a successful campaign. This is in line with the findings of Bourveau et al. (2018), who state that issuers with a minimum funding threshold may not reach their target. Moreover, accepting fiat currencies can boost the marginal effects of ICO success. A potential

explanation, as Momtaz (2020) suggests, is that ICOs that accept fiat currencies allows for easier participation of investors.

Next, we perform the same analysis by using the log of the amount of money raised in the ICO as a dependent variable to reflect the degree of success. Column 2 in Table 2 reports the estimated coefficients with standard errors from cross-sectional regressions employing OLS. The regression results are largely consistent with those of logistic regression. However, the softcap level and accepting fiat currencies during ICO lose their significance in the regression using the log of the amount of money raised as the dependent variable. Furthermore, hardcap and market sentiment measured by CCI30 index positively while number of industry categories negatively impact funds raised.

[Insert Table 2.2 about here.]

After examining the full sample of ICOs, we further focus on three subsamples of our dataset to explore whether there is a change in explanatory factors under different market trends. The subsample results are displayed in Table 3 and 4. Looking at each sub-periods (bullish as well as bearish), things become very different.

Second column in Table 2.3 represents the boom period for the cryptocurrency market. During this period, the coefficient for KYC/Whitelist is negative while the coefficients of CCI30 index and Accepted fiat are positive. These two factors do not have significant impact on fundraising in bust period of cryptocurrency market, as seen in regression 3 and 4. The results can be attributed to enthusiastic investors who jump into ICO projects in boom period. Therefore, higher market sentiment triggers investment towards such a novel area. Similarly, if investors can participate in ICO world in exchange for fiat currency and are not discouraged with the process of pre-ICO registration, the amount raised increases. Moreover, the results show that the impact of “rating” on fundraising is positively significant in the first and second sub-period, while the important criteria is replaced with “number of experts” in the third subperiod. Besides, presale has a positive influence on the fundraising during the cold

period since it is an indicator of the existence of sophisticated investors, which signal strong quality to potential investors during such a period.

[Insert Table 2.3 about here.]

On the other hand, as presented in model 2 of Table 2.4, presales negatively predict ICO success. The justification for this finding proposed by Amsden and Schweizer (2018) is that a campaign conducting presale may be viewed suspicious that there will be enough funds raised in the crowdsale hence disheartening investors from getting involved in ICO projects.

[Insert Table 2.4 about here.]

2.4.2.2. ICO Returns

Once the fundraising for blockchain-related venture through issuance of tokens is completed, aftermarket performance of such tokens needs to be assessed upon being listed in crypto exchanges and then being traded in the secondary market.

The second part of our analysis examines factors associated with ICO returns. Column (1) of Table 5 reports the results where the dependent variable of the model is underpricing as defined above. The first significant determinant of ICO return is the concurrent return of the CCI30. This result is in line with traditional IPO literature (Ljungqvist et al., 2006; Ljungqvist and Wilhelm, 2003; Loughran and Ritter, 2002), showing the importance of market sentiments on stock prices. Similarly, market sentiment around cryptocurrencies is significant driver of investor's decision to invest in growing industry. As long as the cryptocurrency market is hot the investors are more optimistic about the freshly issued altcoins, which may result in underpricing. Moreover, raised amount has a positive relationship to the level of underpricing, which can be attributed to the existence of considerably high demand for the project.

The offer price has a negative influence on the level of underpricing. This result is consistent with the Grinblatt and Hwang (1989)'s theoretical model based on IPO underpricing, according to which the offer price serves as a signal for the true firm value. Similarly, in the ICO context, Benedetti and Kostovetsky (2018) find that the offer price is negatively correlated with underpricing and ICO returns. In the view of the authors, token prices move to a “normal” nominal price level when they are traded.

[Insert Table 2.5 about here.]

Specifically, when we check underpricing under different market conditions, insignificance of amount of raised in first sub-period swings to significance in second and third sub-periods, as displayed in Table 2.6. In addition, the presence of KYC/Whitelist policies could lead underpricing over the sub-period of bull market in cryptocurrency market. US Restriction shows significant positive sign in second sub-period, suggesting that lower risk of potential SEC regulatory intervention associated with higher underpricing in bullish ICO market but bearish cryptocurrency market. Related similar finding is Momtaz (2020) who shows that the number of restricted countries is positively associated with ICO underpricing, suggesting that issuers that choose to reduce the set of potential investors need to offer higher incentives for the remaining.

The coefficients on the end-to-open return and on the first listing day return are significantly negative at all horizons. This result is consistent with fads hypothesis in IPOs, which argues that IPOs may be overpriced on the first day with the optimistic beliefs of investors about prospects of these firms. But in the long run, as the more information is disclosed to the public, the price of IPOs reaches its true value leading to an inverse relation between initial returns and long-term performance of IPOs. More likely to see the potential for such an impact in the case of ICOs as ICO ventures are rather young, immature, and relatively informationally opaque in the absence of mandatory disclosure and hence are hard to quantify the true value.

Moreover, first day return is negatively correlated to end-to-open return. These results suggest that the market corrects the overvaluation tokens once high initial returns are realized. Bourveau et al. (2018) offer another interpretation in the ICO sphere, according to which, significant effect of crypto-market sentiment and first day ICO returns are related with the pump-and-dump strategies by ICO entities in the unregulated crypto field.

[Insert Table 2.6 about here.]

From Table 2.7 to Table 2.12, we display the return behavior regarding bearish and bullish phases, running OLS model for each period on different horizons. Note that, regardless of market conditions, ICO returns are mainly driven by market sentiment and first day return than by characteristics of campaign or company.

2.5. Conclusion

This study complements the growing academic literature on ICOs. We first go over extant literature to look at determinants of fundraising success as well as determinants of the return on Initial Coin Offerings (ICOs) already discovered. After collecting a comprehensive set of measures, we identify the bull and bear phases of the market to assess the sensitivity of our results to the different market conditions.

We connect ICO research to the theories related to IPOs. Empirical analysis shows that ICO success, ICO underpricing and longer-term post-ICO returns are explained with agency theory, signaling, and behavioral theories behind IPOs. However, some findings for ICOs stand in contrast with the respective IPO literature. It is plausible due to substantial differences between the ICOs and IPOs regarding regulation, disclosure requirements, ownership, and uncertainty about consumer demand.

Our evidence suggests that ICOs with higher ratings, larger number of experts, more members in developing team and shorter planned token sale duration have a greater likelihood of success and raising more funds. However, retaining a smaller share,

offering bonus for early investors, and setting higher hardcap levels have negative impact on the success of the campaign. We also show that underpricing can be explained by offer price, market sentiment, raised and ICO duration. Moreover, market sentiment, the offer price, the end-to-open return and the first listing day return have significant impact on aftermarket performance of the ICOs. We further add to the literature about whether the key factors to successful ICO factors and ICO returns differ between boom-and-bust periods. Our empirical findings suggest that market trend matters, and future research should account for that.

Our results have important practical implications, especially for investors who bear risks due to limited investor protection in an unregulated environment. To reduce investment risk, investors should take key considerations on several ICO characteristics such as expert ratings, team members behind the project, the length of the campaign, the proportion available for public sale into account before involving in an ICO. In addition, investors are well-advised to consider experts providing ratings which serve as information intermediaries in financing ICO ventures. It would also be wise for investors to focus on the importance of market sentiment on the success of an ICO and aftermarket performance. Our results further provide insights for ventures seeking to launch an ICO. Such ventures must focus on signaling ICO project quality to attract investors and hence increase the likelihood of the success of the campaign. Namely, ventures that disclose more information are more likely to convince investors to contribute to the project. Specifically, it is important for ventures to time the market, build a great team, develop technological capabilities, and keep ICO duration as short as possible. From the standpoint of policymakers, this research shows that policies that mitigate asymmetric information problem might be needed. Information plays an important role in this new landscape. Thus, policy makers can standardize white paper format describing platform-based business idea, road map, the developer team, the rights a token provides and the token sales. In addition, imposing sanctions prohibits ventures from sending false signals which in turn engenders trust. Similarly, regulators might supervise the experts to ensure that they provide unbiased ratings on ICOs. As such, the value of tokens is more accurately evaluated.

Figure 2.1 displays time-series pattern of ICOs in our sample quarterly. Total funds raised by ICOs are plotted on the right axis, compared to the total number of ICOs with the number of successful and failed ICOs, plotted on the left axis.

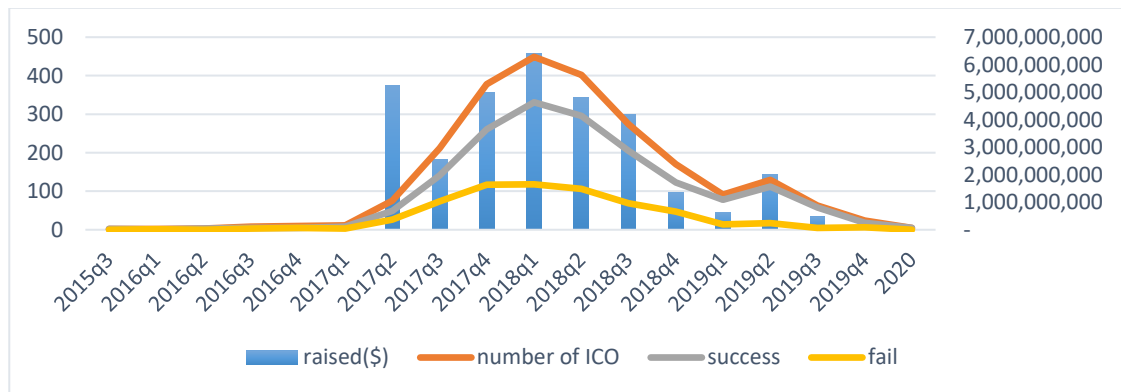


Figure 2.1: The evolution of ICOs

Table 2.1: Descriptive Statistics

<u>Variable</u>	<u>Obs.</u>	<u>Mean</u>	<u>Median</u>	<u>Std. Dev.</u>	<u>Min.</u>	<u>Max.</u>
Amount raised (mio)	2318	14.307	4.2	99.85	0	4197.9
Softcap (mio)	1863	21.3	1	315.208	0	10000
Hardcap (mio)	1817	121.071	20	1044.5	0	30000
ICO Duration	2308	52	31	54.552	1	760
ERC20	2318	0.752	1	0.432	0	1
Rating	2315	3.134	3.2	0.743	0.6	4.8
# Expert	2315	5	1	8.386	0	97
Bonus	2318	0.439	0	0.496	0	1
KYC&Whitelist	2318	0.445	0	0.497	0	1
Presale	2318	0.253	0	0.435	0	1
# Industry categories	2318	2.815	2	2.127	1	12
# Team member	2143	10	9	6.449	1	58
Distributed in ICO	1838	0.513	0.510	0.232	0	1
US investors						
restricted	2318	0.313	0	0.464	0	1
Accepted fiat	2318	0.128	0	0.334	0	1
Major						
cryptocurrencies	2318	0.607	1	0.489	0	1
CCI30(in 1000)	2309	6.207	4.991	3.787	0.088	20.801
Price in ICO	802	14.628	.1	287.458	.0000204	7554.6
Underpricing	802	2.610	-.2056	31.414	-.9999943	709.937
End-to-open return	802	2.434	-.2573	30.434	-.9999957	679
First day return	802	.126	.0132	.684	-.913	15.925
First week return	801	.103	-.0909	1.158	-.966	17.928
1-month return	799	.083	-.2950	1.399	-.994	17.873
3-month return	773	.251	-.4616	2.801	-.998	46.945
6-month return	715	.306	-.7288	3.804	-.9997	42.417
1-year return	599	.187	-.8514	6.619	-.9999956	114.169

Table 2.2: Determinants of ICO Success

This table reports the logit and OLS regression results for the determinants of ICO success. The dependent variable in Model (1) is a binary variable that equals 1 if the ICO hits its softcap or the amount of money raised is more than \$0.5 million in the absence of a soft cap and, 0 otherwise. The dependent variable in Model (2) is Raised (log USD). The independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level. In Model (1), we also report the marginal effects of independent variables.

	(1) Success/Fail	Marg. Eff.	(2) Raised
Softcap	-0.0925*** (0.0116)	-0.0108	-0.0144 (0.00882)
Hardcap	-0.101** (0.0455)	-0.0118	0.321*** (0.0476)
ICO Duration	-0.233*** (0.0704)	-0.0272	-0.301*** (0.0464)
ERC20	0.0226 (0.173)	0.0026	-0.136 (0.131)
Rating	0.238* (0.131)	.0279	0.222* (0.113)
# Expert	0.141* (0.0729)	.0165	0.155** (0.0598)
Bonus	-0.288** (0.137)	-.0339	-0.154* (0.0836)
KYC/Whitelist	0.0227 (0.162)	.0026	-0.106 (0.111)
Presale	-0.134 (0.141)	-.0153	0.0201 (0.108)
# Industry categories	-0.0156 (0.0291)	-.0018	-0.0462** (0.0211)
# Team member	0.313** (0.135)	.0365	0.601*** (0.08)
Distributed in ICO	-0.533* (0.312)	-.0624	-0.662** (0.314)
US investors restricted	-0.0499 (0.143)	-.0058	0.138 (0.121)
Accepted fiat	0.360* (0.214)	.0461	0.101 (0.203)
Major cryptocurrencies	0.0607 (0.157)	.0071	-0.2 (0.143)
CCI30	0.0539 (0.0336)	.0063	0.0372* (0.0197)
Constant			6.948*** (0.998)
Obs.	1452		1459
Adj. R^2			0.164
Pseudo R^2	0.095		
Country/Quarter Fixed Effect	Yes		Yes

Table 2.3: Dependent Variable: Amount Raised

This table reports the coefficient estimates from OLS regression for the entire sample and sub-samples. In each model, the dependent variable is Raised (Log USD). Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. The dependent variable in Model (2) is Raised (log USD). The independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
Softcap	-0.0144 (0.00882)	-0.0557** (0.0238)	-0.0236** (0.00925)	0.0211 (0.0161)
Hardcap	0.321*** (0.0476)	0.0403 (0.0934)	0.332*** (0.0686)	0.386*** (0.0670)
ICO Duration	-0.301*** (0.0464)	-0.377** (0.120)	-0.317*** (0.0716)	-0.223*** (0.0730)
ERC20	-0.136 (0.131)	-0.359 (0.301)	-0.306 (0.191)	0.00709 (0.198)
Rating	0.222* (0.113)	0.805* (0.438)	0.274** (0.122)	-0.0523 (0.186)
# Expert	0.155** (0.0598)	0.248 (0.196)	0.113 (0.0856)	0.178** (0.0841)
Bonus	-0.154* (0.0836)	0.0704 (0.348)	-0.0574 (0.146)	-0.274** (0.112)
KYC/Whitelist	-0.106 (0.111)	-1.518*** (0.501)	0.0295 (0.129)	-0.0743 (0.164)
Presale	0.0201 (0.108)	-0.427 (0.454)	0.0381 (0.151)	0.312** (0.148)
# Industry categories	-0.0462** (0.0211)	0.0903 (0.111)	-0.0836* (0.0425)	-0.00853 (0.0495)
# Team member	0.601*** (0.08)	0.645* (0.321)	0.827*** (0.190)	0.305*** (0.111)
Distributed in ICO	-0.662** (0.314)	-0.941 (0.792)	-0.700 (0.448)	-0.661 (0.413)
US investors restricted	0.138 (0.121)	0.334 (0.255)	0.0454 (0.160)	0.106 (0.204)
Accepted fiat	0.101 (0.203)	0.868* (0.463)	-0.126 (0.254)	0.152 (0.358)
Major cryptocurrencies	-0.2 (0.143)	-0.453 (0.278)	-0.298** (0.148)	-0.110 (0.272)
CCI30	0.0372* (0.0197)	0.0981** (0.0476)	0.0308 (0.0269)	-0.117 (0.0734)
Constant	6.948*** (0.998)	9.172*** (2.598)	8.590*** (1.117)	9.386*** (1.803)
Obs.	1459	252	614	593
Adj. R^2	0.164	0.257	0.190	0.111
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Table 2.4: Dependent Variable: Status (Success/Fail)

This table reports the coefficient estimates from logit regression for the entire sample and sub-samples. In each model, the dependent variable is a binary variable that equals 1 if the ICO hits its softcap or the amount of money raised is more than \$0.5 million in the absence of a soft cap and, 0 otherwise. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. The independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level. For each model, we also report the marginal effects of independent variables.

	(1) (2015Q1-2020M1)	Marg. Eff.(1)	(2) (2015Q1-2017Q4)	Marg. Eff.(2)	(3) (2018Q1-2018Q2)	Marg. Eff.(3)	(4) (2018Q3-2020M1)	Marg. Eff.(4)
Softcap	-0.0925*** (0.0116)	-0.0108	-0.110*** (0.0266)	-.0033	-0.118*** (0.0194)	-.0135	-0.0639*** (0.0186)	.0020
Hardcap	-0.101** (0.0455)	-0.0118	-0.0465 (-0.37)	0.0045	-0.159** (0.0716)	-.0182	-0.0861 (0.0684)	-.0027
ICO Duration	-0.233*** (0.0704)	-.0272	-0.299 (0.266)	-.0091	-0.363*** (0.120)	-.0415	-0.124 (0.0952)	-.0039
ERC20	0.0226 (0.173)	.0026	0.643 (0.399)	.0224	-0.0479 (0.282)	-.0055	-0.0605 (0.283)	-.0019
Rating	0.238* (0.131)	.0279	0.666 (0.445)	.0203	0.470** (0.220)	.0537	0.0204 (0.180)	.0006
# Expert	0.141* (0.0729)	.0165	0.545* (0.303)	.0166	0.0345 (0.114)	.0039	0.116 (0.108)	.0037
Bonus	-0.288** (0.137)	-.0339	-0.103 (0.392)	-.0031	-0.384* (0.218)	-.0446	-0.238 (0.210)	-.0077
KYC/Whitelist	0.0227 (0.162)	.0026	-1.345 -1.064	-.0752	0.141 (0.232)	.0159	0.147 (0.245)	.0045
Presale	-0.134 (0.141)	-.0153	-1.169** (0.530)	-.0554	-0.133 (0.213)	-.015	0.0526 (0.207)	.0017
# Industry categories	-0.0156 (0.0291)	-.0018	0.176 (0.165)	.0053	-0.0654 (0.0459)	-.0074	0.0105 (0.0401)	.0003
# Team member	0.313** (0.135)	.0365	0.680* (0.405)	.0207	0.740*** (0.225)	.0846	-0.0777 (0.196)	-.0024
Distributed in ICO	-0.533* (0.312)	-.0624	-0.471 (0.869)	-.014	-0.213 (0.504)	-.0243	-0.769 (0.471)	-.0246
US investors restricted	-0.0499 (0.143)	-.0058	0.501 (0.917)	.0127	-0.175 (0.219)	-.0198	-0.0699 (0.203)	-.0022
Accepted fiat	0.360* (0.214)	.0461	0.473 -1.167	.0120	0.660* (0.338)	.089	-0.00599 (0.299)	-.0002
Major cryptocurrencies	0.0607 (0.157)	.0071	-0.709 (0.470)	-.0191	0.351 (0.242)	.0391	-0.148 (0.246)	-.0048
CCI30	0.0539 (0.0336)	.0063	0.240** (0.120)	.0073	0.0312 (0.0397)	.0035	-0.0644 (0.129)	-.0021
Obs.	1452		260		614		592	
Adj. R^2	0.095		0.277		0.148		0.048	
Country/Quarter fixed effect	Yes		Yes		Yes		Yes	

Table 2.5: ICO Performance

This table provides the regression of determinants of aftermarket returns at different horizons: underpricing (end-to-close return), first day (open-to-end) return, 1-week, 1-month, 3-month, 6-month and 1-year returns. CCI30 returns are used for the corresponding return intervals as the dependent variables. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) Underpricing	(2) First day ret	(3) 1-week ret	(4) 1-month ret	(5) 3-month ret	(6) 6-month ret	(7) 1-year ret
ICO end-to-open return		-0.0174 [*] (0.00975)	-0.0661 ^{***} (0.0163)	-0.121 ^{***} (0.0239)	-0.177 ^{***} (0.0279)	-0.201 ^{***} (0.0396)	-0.228 ^{***} (0.0480)
First day return			-0.400 ^{***} (0.111)	-0.644 ^{***} (0.110)	-0.767 ^{***} (0.153)	-0.865 ^{***} (0.239)	-1.090 ^{***} (0.223)
End-to-close CCI30 return	0.763 ^{***} (0.118)						
1-day CCI30 return		0.519 ^{***} (0.185)					
1-week CCI30 return			0.117 ^{***} (0.0333)				
1-month CCI30 return				0.324 ^{***} (0.0612)			
3-month CCI30 return					0.532 ^{***} (0.0459)		
6-month CCI30 return						0.881 ^{***} (0.101)	
1-year CCI30 return							1.471 ^{***} (0.295)
Raised	0.137 ^{***} (0.0503)	-0.0217 ^{**} (0.00937)	-0.0211 (0.0174)	-0.0302 (0.0211)	-0.00699 (0.0300)	0.00617 (0.0423)	0.0430 (0.0572)
Price ICO	-0.724 ^{***} (0.266)	-0.0245 [*] (0.0131)	-0.104 ^{***} (0.0365)	-0.158 ^{**} (0.0717)	-0.237 ^{***} (0.0730)	-0.327 ^{***} (0.0999)	-0.286 ^{***} (0.100)
ICO Duration	-0.169 ^{***} (0.0400)	0.00639 (0.00861)	0.00656 (0.0156)	0.0115 (0.0245)	-0.0110 (0.0277)	-0.0410 (0.0455)	-0.0802 (0.0577)
ERC20	-0.0656 (0.137)	-0.0186 (0.0154)	-0.0482 (0.0625)	-0.111 (0.0865)	-0.0535 (0.0942)	-0.0330 (0.120)	-0.111 (0.194)
Rating	0.0514 (0.104)	-0.0322 (0.0218)	0.0461 (0.0451)	-0.0143 (0.0531)	0.0227 (0.0696)	0.338 ^{***} (0.110)	0.441 ^{***} (0.109)
# Expert	-0.0468 (0.0605)	0.00490 (0.00780)	-0.0721 ^{***} (0.0255)	-0.0482 (0.0385)	-0.0732 (0.0461)	-0.151 ^{***} (0.0451)	-0.144 (0.0887)
Bonus	-0.170 (0.179)	-0.0261 (0.0183)	-0.0540 (0.0567)	-0.0339 (0.0976)	-0.0440 (0.114)	-0.125 (0.141)	-0.0846 (0.196)
KYC&Whitelist	0.305 (0.263)	-0.00754 (0.0325)	0.0737 [*] (0.0394)	0.209 ^{***} (0.0645)	0.244 [*] (0.124)	0.128 (0.218)	0.165 (0.287)
Presale	-0.106 (0.191)	0.0419 (0.0270)	-0.0588 (0.0457)	-0.0223 (0.0737)	-0.0837 (0.148)	0.0832 (0.151)	0.134 (0.251)
# Industry categories	-0.0456 [*] (0.0270)	0.00117 (0.00653)	-0.0105 (0.00651)	-0.0159 (0.0112)	-0.0281 (0.0179)	0.0126 (0.0340)	-0.0409 (0.0465)
# Team members	-0.00584 (0.0766)	0.00187 (0.0136)	-0.0651 [*] (0.0339)	-0.0823 [*] (0.0427)	-0.112 (0.0740)	-0.254 ^{***} (0.0846)	-0.195 (0.122)
Distributed in ICO	-0.193 (0.219)	-0.0373 (0.0326)	0.228 ^{**} (0.0990)	0.0400 (0.118)	0.205 (0.161)	0.0743 (0.206)	0.228 (0.257)
US investors restricted	-0.164 (0.120)	-0.0525 ^{***} (0.0165)	0.0427 (0.0513)	0.0195 (0.0779)	0.220 [*] (0.111)	0.242 [*] (0.142)	0.349 (0.255)
Accepted fiat	0.204 (0.198)	0.0220 (0.0347)	-0.0150 (0.0766)	0.157 (0.144)	0.253 (0.183)	0.0357 (0.206)	-0.0167 (0.268)
Major cryptocurrencies	0.0412 (0.115)	0.0425 (0.0264)	0.0229 (0.0391)	0.0560 (0.0526)	-0.0439 (0.0902)	-0.112 (0.118)	-0.164 (0.189)
Constant	0.170 (0.717)	0.321 [*] (0.161)	0.628 ^{***} (0.215)	1.118 ^{***} (0.323)	1.634 ^{***} (0.416)	2.465 ^{***} (0.452)	3.001 ^{**} (1.486)
Observations	672	672	672	671	654	615	526
Adjusted R^2	0.242	0.081	0.105	0.171	0.299	0.351	0.346
Country/Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.6: Underpricing

This table provides the regression of determinants of underpricing (end-to-close return) for the entire sample and sub-samples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
End-to-close CCI30 return	0.763*** (0.118)	0.528*** (0.0995)	1.969*** (0.315)	1.418** (0.539)
Raised	0.137*** (0.0503)	0.0959 (0.0701)	0.263** (0.113)	0.103** (0.0491)
Price ICO	-0.724*** (0.266)	-0.611** (0.238)	-1.384*** (0.369)	-0.148 (0.697)
ICO Duration	-0.169*** (0.0400)	-0.247*** (0.0710)	-0.236*** (0.0646)	0.0122 (0.132)
ERC20	-0.0656 (0.137)	-0.626*** (0.195)	-0.144 (0.211)	0.295 (0.361)
Rating	0.0514 (0.104)	0.172 (0.143)	0.134 (0.254)	-0.167 (0.296)
# Expert	-0.0468 (0.0605)	0.104 (0.101)	-0.189 (0.155)	0.0413 (0.126)
Bonus	-0.170 (0.179)	-0.218 (0.215)	-0.0396 (0.238)	-0.0951 (0.355)
KYC&Whitelist	0.305 (0.263)	0.784*** (0.278)	0.0121 (0.280)	0.308 (0.409)
Presale	-0.106 (0.191)	0.325 (0.579)	-0.0474 (0.244)	-0.194 (0.498)
# Industry categories	-0.0456* (0.0270)	0.00112 (0.0608)	-0.0249 (0.0475)	-0.138** (0.0572)
# Team members	-0.00584 (0.0766)	-0.265** (0.108)	0.482** (0.226)	-0.383 (0.262)
Distributed in ICO	-0.193 (0.219)	0.173 (0.311)	-0.455 (0.440)	-0.558 (0.935)
US investors restricted	-0.164 (0.120)	-0.236 (0.363)	0.306* (0.182)	-0.465 (0.636)
Accepted fiat	0.204 (0.198)	0.880*** (0.314)	-0.479 (0.320)	0.247 (0.659)
Major cryptocurrencies	0.0412 (0.115)	0.149 (0.120)	-0.236 (0.226)	0.319 (0.361)
Constant	0.170 (0.717)	0.646 (1.011)	-4.475** (2.204)	-0.274 (1.071)
Observations	672	271	258	143
Adjusted R ²	0.242	0.324	0.367	0.095
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Table 2.7: First day return

This table provides the regression of determinants of first day (open-to-end) return for the entire sample and subsamples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
ICO end-to-open return	-0.0174* (0.00975)	-0.0124 (0.0107)	0.000174 (0.00991)	-0.0204 (0.0133)
1-day CCI30 return	0.519*** (0.185)	0.415** (0.192)	0.230 (0.233)	1.122** (0.441)
Raised	-0.0217** (0.00937)	-0.0215** (0.00891)	-0.0205** (0.00956)	-0.0476 (0.0300)
Price ICO	-0.0245* (0.0131)	-0.0208 (0.0148)	-0.000384 (0.0204)	-0.0523*** (0.0191)
ICO Duration	0.00639 (0.00861)	0.00277 (0.0104)	0.00917 (0.0140)	-0.00135 (0.00873)
ERC20	-0.0186 (0.0154)	-0.0304* (0.0155)	0.0174 (0.0268)	-0.105*** (0.0389)
Rating	-0.0322 (0.0218)	-0.0528* (0.0286)	0.0154 (0.0410)	-0.106** (0.0470)
# Expert	0.00490 (0.00780)	0.0116 (0.0116)	0.0115 (0.0302)	-0.00303 (0.0250)
Bonus	-0.0261 (0.0183)	-0.0163 (0.0189)	-0.0888*** (0.0275)	0.0487 (0.0391)
KYC&Whitelist	-0.00754 (0.0325)	-0.0201 (0.0460)	0.0423 (0.133)	-0.0359 (0.0511)
Presale	0.0419 (0.0270)	0.0473 (0.0353)	0.0448 (0.0871)	0.0480 (0.0458)
# Industry categories	0.00117 (0.00653)	-0.00245 (0.0107)	-0.00834 (0.0125)	-0.00437 (0.0121)
# Team members	0.00187 (0.0136)	0.00372 (0.0145)	-0.00316 (0.0318)	0.00683 (0.0159)
Distributed in ICO	-0.0373 (0.0326)	-0.0556 (0.0368)	-0.0637 (0.0505)	-0.0154 (0.0654)
US investors restricted	-0.0525*** (0.0165)	-0.0590*** (0.0217)	-0.118** (0.0536)	-0.0131 (0.0326)
Accepted fiat	0.0220 (0.0347)	0.0101 (0.0467)	0.0713 (0.0682)	-0.0782 (0.0657)
Major cryptocurrencies	0.0425 (0.0264)	0.0423 (0.0321)	0.0721 (0.0447)	-0.00914 (0.0468)
Constant	0.321* (0.161)	0.372* (0.196)	0.166 (0.181)	1.331** (0.564)
Observations	672	529	271	258
Adjusted R^2	0.081	0.074	0.074	0.142
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: First week return

This table provides the regression of determinants of 1-week return for the entire sample and sub-samples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
ICO end-to-open return	-0.0661*** (0.0163)	-0.105*** (0.0293)	-0.102** (0.0416)	0.0464* (0.0268)
First day return	-0.400*** (0.111)	-0.637*** (0.128)	-0.226 (0.247)	0.190 (0.149)
1-week CCI30 return	0.117*** (0.0333)	0.164*** (0.0358)	0.160* (0.0930)	-0.0648 (0.146)
Raised	-0.0211 (0.0174)	-0.0352 (0.0267)	0.0201 (0.0274)	-0.00487 (0.0178)
Price ICO	-0.104*** (0.0365)	-0.134** (0.0504)	-0.172** (0.0823)	0.433** (0.199)
ICO Duration	0.00656 (0.0156)	-0.0283 (0.0272)	0.0526** (0.0240)	-0.0630 (0.0471)
ERC20	-0.0482 (0.0625)	-0.0844 (0.0937)	-0.0180 (0.0912)	-0.134 (0.0872)
Rating	0.0461 (0.0451)	0.121* (0.0700)	0.0129 (0.0618)	0.142 (0.0938)
# Expert	-0.0721*** (0.0255)	-0.0577 (0.0444)	-0.0671** (0.0316)	-0.138** (0.0557)
Bonus	-0.0540 (0.0567)	-0.0652 (0.0981)	0.00505 (0.0705)	0.00611 (0.110)
KYC&Whitelist	0.0737* (0.0394)	-0.274 (0.186)	0.0972 (0.0586)	0.209 (0.135)
Presale	-0.0588 (0.0457)	-0.244* (0.140)	0.0535 (0.0439)	-0.203** (0.0908)
# Industry categories	-0.0105 (0.00651)	-0.0294 (0.0301)	-0.0114 (0.0153)	-0.0130 (0.0211)
# Team members	-0.0651* (0.0339)	-0.0642 (0.0473)	-0.0555* (0.0303)	-0.0518 (0.0844)
Distributed in ICO	0.228** (0.0990)	0.189* (0.110)	0.141* (0.0797)	0.286 (0.197)
US investors restricted	0.0427 (0.0513)	0.00468 (0.126)	0.0188 (0.0815)	0.0108 (0.159)
Accepted fiat	-0.0150 (0.0766)	0.0166 (0.188)	0.0328 (0.0996)	-0.0287 (0.151)
Major cryptocurrencies	0.0229 (0.0391)	0.101 (0.0751)	0.0708 (0.0585)	-0.136 (0.166)
Constant	0.628*** (0.215)	0.743** (0.332)	-0.657 (0.545)	-0.0712 (0.493)
Observations	672	271	258	143
Adjusted R^2	0.105	0.157	0.131	0.247
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2. 9: First month return

This table provides the regression of determinants of 1-month return for the entire sample and sub-samples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
ICO end-to-open return	-0.121*** (0.0239)	-0.174*** (0.0620)	-0.168*** (0.0466)	0.0251 (0.0434)
First day return	-0.644*** (0.110)	-1.089*** (0.240)	-0.317 (0.279)	-0.245 (0.212)
1-month CCI30 return	0.324*** (0.0612)	0.416*** (0.0732)	0.328*** (0.0891)	0.149 (0.344)
Raised	-0.0302 (0.0211)	-0.0629** (0.0273)	0.0100 (0.0413)	0.0222 (0.0344)
Price ICO	-0.158** (0.0717)	-0.186* (0.110)	-0.191 (0.128)	0.352 (0.361)
ICO Duration	0.0115 (0.0245)	-0.0744 (0.0609)	0.0982** (0.0375)	-0.0897 (0.0688)
ERC20	-0.111 (0.0865)	-0.201 (0.122)	-0.0508 (0.0928)	-0.0974 (0.159)
Rating	-0.0143 (0.0531)	0.119 (0.0874)	-0.00866 (0.0645)	0.282*** (0.103)
# Expert	-0.0482 (0.0385)	-0.0121 (0.0711)	-0.0670 (0.0462)	-0.236*** (0.0751)
Bonus	-0.0339 (0.0976)	-0.0439 (0.173)	0.0319 (0.105)	0.234 (0.142)
KYC&Whitelist	0.209*** (0.0645)	-0.197 (0.341)	0.235*** (0.0862)	0.398* (0.217)
Presale	-0.0223 (0.0737)	-0.199 (0.207)	0.0111 (0.0882)	-0.175 (0.205)
# Industry categories	-0.0159 (0.0112)	-0.0767 (0.0622)	0.00528 (0.0301)	-0.0286 (0.0373)
# Team members	-0.0823* (0.0427)	-0.128 (0.115)	0.0191 (0.0700)	-0.0850 (0.148)
Distributed in ICO	0.0400 (0.118)	-0.310* (0.180)	0.245** (0.110)	0.551* (0.313)
US investors restricted	0.0195 (0.0779)	-0.132 (0.191)	0.110 (0.111)	-0.232 (0.215)
Accepted fiat	0.157 (0.144)	0.253 (0.391)	0.0474 (0.146)	0.452** (0.178)
Major cryptocurrencies	0.0560 (0.0526)	0.255*** (0.0740)	0.0592 (0.0742)	-0.189 (0.141)
Constant	1.118*** (0.323)	1.603*** (0.492)	-1.356* (0.784)	-1.100 (0.899)
Observations	671	271	258	142
Adjusted R^2	0.171	0.281	0.160	0.191
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: 3-month return

This table provides the regression of determinants of 3-month return for the entire sample and sub-samples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
ICO end-to-open return	-0.177*** (0.0279)	-0.250*** (0.0592)	-0.194*** (0.0414)	-0.0133 (0.0527)
First day return	-0.767*** (0.153)	-0.925*** (0.268)	-0.733*** (0.166)	-0.782** (0.293)
3-month CCI30 return	0.532*** (0.0459)	0.575*** (0.0529)	0.377*** (0.121)	0.448 (0.503)
Raised	-0.00699 (0.0300)	-0.0614 (0.0366)	0.0994 (0.0696)	0.0789 (0.0501)
Price ICO	-0.237*** (0.0730)	-0.304*** (0.100)	-0.253 (0.162)	-0.206 (0.430)
ICO Duration	-0.0110 (0.0277)	-0.108* (0.0583)	0.0590 (0.0353)	-0.0353 (0.0545)
ERC20	-0.0535 (0.0942)	-0.113 (0.133)	-0.315** (0.147)	0.178 (0.192)
Rating	0.0227 (0.0696)	0.298** (0.124)	-0.00938 (0.0847)	0.124 (0.169)
# Expert	-0.0732 (0.0461)	-0.0909 (0.111)	-0.0945 (0.0614)	-0.387*** (0.0960)
Bonus	-0.0440 (0.114)	0.0166 (0.179)	-0.0916 (0.146)	0.281 (0.195)
KYC&Whitelist	0.244* (0.124)	0.146 (0.446)	0.0134 (0.200)	0.916*** (0.210)
Presale	-0.0837 (0.148)	-0.375 (0.307)	0.0785 (0.223)	-0.195 (0.322)
# Industry categories	-0.0281 (0.0179)	-0.0917 (0.0772)	0.0180 (0.0504)	-0.0753** (0.0329)
# Team members	-0.112 (0.0740)	-0.0862 (0.128)	-0.0457 (0.126)	0.0418 (0.231)
Distributed in ICO	0.205 (0.161)	-0.0507 (0.152)	0.714*** (0.233)	0.439 (0.380)
US investors restricted	0.220* (0.111)	-0.173 (0.204)	0.409*** (0.140)	0.167 (0.180)
Accepted fiat	0.253 (0.183)	0.0260 (0.445)	0.310* (0.155)	0.100 (0.301)
Major cryptocurrencies	-0.0439 (0.0902)	0.135 (0.164)	0.0702 (0.101)	-0.462* (0.232)
Constant	1.634*** (0.416)	2.018*** (0.485)	-2.766* (1.407)	-2.679** (1.101)
Observations	654	269	256	129
Adjusted R^2	0.299	0.355	0.161	0.301
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: 6-month return

This table provides the regression of determinants of 6-month return for the entire sample and sub-samples. Model (1), Model (2), Model (3) and Model (4) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4, 2018Q1-2018Q2 and 2018Q3-2020M1, respectively. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2	(4) 2018Q3-2020M1
ICO end-to-open return	-0.201*** (0.0396)	-0.242*** (0.0581)	-0.0680 (0.0508)	-0.173** (0.0642)
First day return	-0.865*** (0.239)	-1.187*** (0.359)	-0.750*** (0.256)	-1.251** (0.475)
6-month CCI30 return	0.881*** (0.101)	0.921*** (0.0975)	-0.112 (0.354)	1.873 (1.164)
Raised	0.00617 (0.0423)	0.00287 (0.0456)	0.104 (0.0755)	0.0134 (0.0878)
Price ICO	-0.327*** (0.0999)	-0.427*** (0.159)	0.0217 (0.129)	0.155 (1.073)
ICO Duration	-0.0410 (0.0455)	-0.128* (0.0693)	0.0471 (0.0503)	-0.0464 (0.106)
ERC20	-0.0330 (0.120)	-0.0152 (0.168)	-0.390* (0.210)	-0.263 (0.540)
Rating	0.338*** (0.110)	0.665** (0.252)	0.141 (0.0875)	0.764** (0.343)
# Expert	-0.151*** (0.0451)	-0.317*** (0.108)	-0.146** (0.0601)	-0.317 (0.217)
Bonus	-0.125 (0.141)	-0.101 (0.237)	-0.0608 (0.205)	0.0340 (0.355)
KYC&Whitelist	0.128 (0.218)	-0.385 (0.358)	-0.130 (0.272)	0.640** (0.302)
Presale	0.0832 (0.151)	-0.478 (0.371)	0.216 (0.234)	-0.199 (0.324)
# Industry categories	0.0126 (0.0340)	-0.0135 (0.0745)	0.0384 (0.0652)	-0.0578 (0.0540)
# Team members	-0.254*** (0.0846)	-0.272 (0.195)	-0.153 (0.144)	-0.201 (0.275)
Distributed in ICO	0.0743 (0.206)	-0.317 (0.230)	0.928** (0.424)	0.880 (0.845)
US investors restricted	0.242* (0.142)	-0.340 (0.336)	0.748*** (0.165)	-0.220 (0.385)
Accepted fiat	0.0357 (0.206)	0.0258 (0.446)	0.165 (0.213)	-0.980* (0.508)
Major cryptocurrencies	-0.112 (0.118)	0.297* (0.170)	-0.0819 (0.137)	-1.067** (0.447)
Constant	2.465*** (0.452)	2.225** (1.046)	-3.629** (1.663)	-2.352 (2.526)
Observations	615	268	249	98
Adjusted R^2	0.351	0.420	0.142	0.171
Country/Quarter fixed effect	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: 1-year return

This table provides the regression of determinants of 1-year return for the entire sample and sub-samples. Model (1), Model (2) and Model (3) comprise the periods 2015Q3-2020M1, 2015Q3-2017Q4 and 2018Q1-2018Q2, respectively. Since the number of observations for the period 2018Q3-2020M1 is too low, we don't run the regression for this period. CCI30 return is used for the corresponding return interval as the dependent variable. All other independent variables are explained in detail in Section 3.2.2. Coefficient estimates are reported with their standard errors adjusted for heteroskedasticity and clustered by at the quarter level.

	(1) 2015Q3-2020M1	(2) 2015Q3-2017Q4	(3) 2018Q1-2018Q2
ICO end-to-open return	-0.228*** (0.0480)	-0.262*** (0.0706)	-0.0721 (0.0873)
First day return	-1.090*** (0.223)	-1.254*** (0.333)	-1.153*** (0.315)
1-year CCI30 return	1.471*** (0.295)	1.343*** (0.343)	2.003** (0.803)
Raised	0.0430 (0.0572)	0.0278 (0.0513)	0.0513 (0.107)
Price ICO	-0.286*** (0.100)	-0.287** (0.130)	-0.101 (0.162)
ICO Duration	-0.0802 (0.0577)	-0.0786 (0.0956)	-0.00231 (0.0772)
ERC20	-0.111 (0.194)	-0.0773 (0.176)	-0.192 (0.325)
Rating	0.441*** (0.109)	0.711*** (0.170)	0.422* (0.217)
# Expert	-0.144 (0.0887)	-0.179 (0.161)	-0.268* (0.140)
Bonus	-0.0846 (0.196)	-0.177 (0.231)	0.0804 (0.295)
KYC&Whitelist	0.165 (0.287)	0.228 (0.374)	-0.234 (0.425)
Presale	0.134 (0.251)	-0.136 (0.466)	0.281 (0.350)
# Industry categories	-0.0409 (0.0465)	-0.100 (0.0827)	0.0118 (0.0789)
# Team members	-0.195 (0.122)	-0.193 (0.224)	-0.210 (0.238)
Distributed in ICO	0.228 (0.257)	-0.206 (0.236)	1.050* (0.578)
US investors restricted	0.349 (0.255)	-0.567 (0.387)	0.912*** (0.277)
Accepted fiat	-0.0167 (0.268)	0.134 (0.517)	-0.254 (0.420)
Major cryptocurrencies	-0.164 (0.189)	0.181 (0.216)	-0.362 (0.293)
Constant	3.001** (1.486)	2.422 (1.700)	-3.560* (2.104)
Observations	526	267	234
Adjusted R ²	0.346	0.471	0.141
Country/Quarter fixed effect	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER III

INTRADAY EFFICIENCY-FREQUENCY NEXUS IN THE CRYPTOCURRENCY MARKETS

3.1. Introduction

In today's global financial markets, cryptocurrencies, of which Bitcoin is the most prominent example, have been subject to noteworthy interest by theorists, analysts, traders and regulators. The exponential growth of their values coincides with the increased attention in media and finance literature, and moreover, they are acted as a new type of financial assets lately. Many central banks are now exploring new payment technologies, including cryptocurrencies and planning to launch their own digital currencies in order to better understand the principles and potential benefits. Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE) have begun to trade futures contracts on Bitcoin in December 2017. In a first for a major U.S. bank, J.P.Morgan launched its own cryptocurrency in February 2019.³ The latest move by Facebook with its coin Libra has led companies around the world to consider cryptocurrency offering as a potential strategy.

Although cryptocurrencies have attracted special attention from academics and practitioners, there lacks a comprehensive study towards the intraday dynamics of cryptocurrencies, and worse, these research have almost exclusively focused on Bitcoin. Among these, Urquhart (2016); Nadarajah and Chu (2017); Bariviera (2017); Yonghong et al. (2018); Vidal-Tomas and Ibanez (2018); Turattio et al. (2019);

³ <https://www.nytimes.com/2019/02/14/business/dealbook/jpmorgan-cryptocurrency-bitcoin.html>

Gerritsen et al. (2019) investigate whether time varying behaviour of Bitcoin is predictable, which would be inconsistent with the Efficient Market Hypothesis (EMH) proposing that prices should follow a random walk (Fama, 1970). The same question has been analyzed at the intraday level by Sensoy (2019); Corbet et al. (2019); Akyildirim et al. (2019). Such an analysis is uttermost important since any predictable patterns open the doors for trading strategies that can beat the market and generate abnormal returns.

In the last decade, many studies have investigated Bitcoin from several perspectives. While a small group of studies such as Dwyer (2015); Bariviera (2017) focus on the technical aspects and stylized facts of Bitcoin, majority of the studies has focused on the impacts of including Bitcoin to the portfolio and test whether it would be plausible to include this virtual currency in optimal portfolios (Molnar et al., 2015; Popper, 2015; Gangwal, 2016; Baur et al., 2018). The benefits of including Bitcoin in portfolios have been emphasized further by Dyhrberg (2016); Bouri et al. (2017, 2018).

In addition to these studies, a growing strand of literature (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017) investigates whether time varying behavior of Bitcoin is predictable, which would be inconsistent with the Efficient Market Hypothesis (EMH) proposing that prices should follow a random walk (Fama (1970)).

Despite extensive research on the efficiency of Bitcoin, only a few other studies have investigated the return predictability of alternative cryptocurrencies. The majority of these studies provide evidence for inefficiency in cryptocurrency markets (Bouri et al., 2018; Brauneis and Mestel, 2018; Caporale et al., 2018; Phillip et al., 2018; Wei, 2018; Zhang et al., 2018; Chaim and Laurini, 2019; Charfeddine and Maouchi, 2019; Kochling et al., 2019; Hu et al., 2019; Mensi et al., 2019a,b). To the best of our knowledge, only the work by Mensi et al. (2019b) uses high-frequency data of an alternative coin (Ethereum) in order to examine its long memory and weak-form efficiency property.

In this paper, we examine the weak-form efficiency property of four major cryptocurrencies, namely, Bitcoin, Ethereum, Ripple and Litecoin. We employ three

strong methods (R/S, GHE and GPH) to estimate the Hurst exponent and test whether (i) efficiency depends on sampling frequency, (ii) there is an optimal sampling frequency that maximizes weak-form market efficiency, and (iii) optimal frequency differs from one cryptocurrency to another.

This study fills four gaps in the literature. First, the efficiency of Bitcoin has been examined in some depth yet other cryptocurrencies have so far been ignored. We investigate the efficiency of four most capitalized cryptocurrencies, including the Bitcoin.

Second, instead of using daily data like most of the previous studies do, we go down to high frequency level since algorithmic (especially high frequency) trading dominates the trading scene in today's modern financial markets. Moreover, high frequency data is more informative compared to the daily data and may yield more clear picture regarding portfolio analysis and risk management. From the point of the EMH, high frequency data has the edge over the traditional daily data in the empirical study of informational efficiency.

Third, there is a notable lack of studies examining the efficiency in cryptocurrency market for various time intervals. Ongoing literature on the efficiency mostly focused on price observations drawn at fixed time intervals. For example, Eross et al. (2019) decide to select 5-min frequency since they claim that due to noise trading, any higher frequency data is not as liquid compared to 5-min data which may lead to unreliable and spurious results. We, on the other hand, analyze the weak form efficiency in cryptocurrency markets at intervals of 1 minute, 5, 10, 15, 30 and 60 minutes. Goodhart and O'Hara (1997) argue that it is important to use high enough frequency to capture intraday dynamics of the data, but at the same time low enough to avoid any undue noise. In that sense, we characterize the optimal trading frequency for efficiency in this dynamic market using various time intervals. To the best of our knowledge, such kind of an analysis has not been done by previous studies within this context.

Fourth, we employ three various powerful and contrasting tests (Rescaled Range (R/S) statistic, semi parametric GPH statistic and Generalized Hurst Exponent

method) for randomness in order to prevent spurious results and to capture all the dynamics of those cryptocurrencies.

Our findings can be summarized as follows: (i) the efficiency in the cryptocurrency markets varies across frequencies, (ii) sample cryptocurrencies achieve maximum market efficiency around 5- min and 10-min sampling frequencies, thus there is a U-shaped pattern, and (iii) investors employing trading strategies are more likely to generate abnormal profits in the sample cryptocurrencies making trades on either very short (1-minute) or the longest (60-minute) sampling basis.

3.2. Methodology

We use the Hurst exponent H to measure long-range dependence.⁴ Accordingly, the Hurst exponent lies in the interval $[0,1]$. On the basis of the H values, three categories can be identified:

(i) the series are mean-reverting, returns are negatively correlated ($0 \leq H < 0.5$); (ii) the series are random, returns are uncorrelated, thus there is no long-memory in the series ($H = 0.5$); and (iii) the series are persistent, returns are positively correlated ($0.5 < H \leq 1$). Accordingly, while items (i) and (iii) imply inefficiency, item (ii) implies weak form efficient property of the analyzed time series.

We utilize three differing methods to estimate the Hurst exponents for four cryptocurrencies at six intraday sampling frequencies. The selected methods include rescaled range analysis (Hurst, 1951), the Geweke and Porter-Hudak (1983) estimator, and the generalized Hurst exponent (Barabasi and Vicsek, 1991). The following section briefly describes each method.

⁴ Hurst exponent is a more robust tool to measure market efficiency compared to simple measures of autocorrelation or variance ratio tests. The autocorrelation function is inadequate in explaining non-linear temporal dependence in a series. Besides, it is sensitive to abrupt shifts or jumps in mean or volatility. On the other hand, variance ratio tests assumes normality of the data. In addition, these tests are asymptotic and hence for a finite sample, the sampling distributions of the test statistics are approximated based on its limiting distributions.

3.2.1. Rescaled range analysis (R/S)

Rescaled range analysis (R/S) was introduced by Hurst (1951) and further augmented by Mandelbrot (1972, 1975), Mandelbrot and Taqqu (1979) and Mandelbrot and Wallis (1968, 1969a,b) in order to test for long memory property in time series.

To determine the difference between minimum and maximum values of running sums of deviations from the sample mean, renormalized by the sample standard deviation is the purpose behind the classical R/S test. The deviations are larger in case there is long-term memory.

As discussed by Mandelbrot and Taqqu (1979) and Taqqu et al. (1995), for a time series $\{X_t\}_{t \in T}$, $T = \{1, \dots, N\}$, with partial sum $Y(n) = \sum_{i=1}^n X_i$, $n = 1, \dots, N$, and sample variance $S^2(n) = (1/n) \sum_{i=1}^n X_i^2 - (1/n)^2 Y(n)^2$, the R/S statistic, or the rescaled adjusted range, is given by:

$$\frac{R}{S}(n) = \frac{1}{S(n)} \left[\max_{0 \leq t \leq n} \left(Y(t) - \frac{t}{n} Y(n) \right) - \min_{0 \leq t \leq n} \left(Y(t) - \frac{t}{n} Y(n) \right) \right].$$

To calculate H for a return series of length T, we divide the series into N contiguous sub-periods with length v, where $N_v = T$. For each sub-period, we calculate the mean value and construct the mean adjusted series, and cumulative deviate series. We then calculate the range, which is defined as the maximum value of the profile minus the minimum of the profile, and the standard deviation of the original time series for each sub-period. Each range is normalized by dividing by the corresponding standard deviation and forms a rescaled range so that the average rescaled range for a given sub-period of length $(R/S)_v$ is obtained.

The rescaled range scales as $(R/S)_v \approx c v^H$, where c is a finite constant independent of v (Di Matteo, 2007; Taqqu et al., 1995). To uncover the scaling law, simple ordinary least squares regression is used to estimate the equation $\log(R/S)_v = \log(c) + H \log(v)$, where the slope coefficient is the estimate of the Hurst exponent.

3.2.2. Geweke and Porter-Hudak (GPH) model

The second method used to calculate H is the log-periodogram estimator (also known as GPH estimator) of Geweke and Porter-Hudak (1983) which is one of the widespread semiparametric estimation methods. The GPH estimator of the long memory parameter, d , is obtained from the application of the simple linear regression based on periodogram. The periodogram is defined as:

$$I(\lambda_k) = \frac{1}{2\pi T} \left| \sum_{j=1}^n X_j e^{ij\lambda_k} \right|^2.$$

In this setup, $I(\lambda_k)$ stands for the k^{th} periodogram point and it is defined as the squared absolute values of the Fourier transform of the time series X_j . The estimate d is determined running OLS on $\log(I(\lambda_k)) = a - d \log\{4\sin^2(\lambda_k/2)\} + \varepsilon_k$ where $\lambda_k = 2\pi k/N$, $k = 1, 2, \dots, n$; ε_k is the residual term and λ_k represents the $n = \sqrt{N}$ Fourier frequencies. The Hurst exponent equals to $d + 0.5$. Namely, the null hypothesis in GPH test is that 'there is no long memory ($d = 0$)'.

Using synthetic data, Geweke and Porter-Hudak (1983) developed the asymptotic theory which proved to be reliable in samples of 50 observations or more. Namely, the conventional interpretation of the least squares statistics is reasonable in large samples.

3.2.3. Generalized Hurst Exponent approach

The third method used to generate the parameter H is the generalized Hurst exponent (GHE) which was introduced by Barabasi and Vicsek (1991). Di Matteo et al. (2003) re-explored this method for financial time series which is based on scaling of q -th order moments of the distribution of the increments. The GHE is a generalization of the approach proposed by Hurst (1951). The q -th order moment of the distribution of the increments of the stochastic variable $S(t)$, with $t = (1, 2, \dots, \Delta t)$ is given by

$K_q(\tau) = \frac{\langle |S(t+\tau) - S(t)|^q \rangle}{|S(t)|^q}$ where τ can vary between 1 and $\tau_{\max}$ and $\langle \dots \rangle$ denotes the sample average over the time window. The generalized Hurst exponent $H(q)$ is defined for each time scale τ and each parameter q as $K_q(\tau) \propto \tau^{qH(q)}$.

For $q = 1$, $H(1)$ characterizes the scaling behaviour of the absolute increments and is very similar to the original Hurst exponent. The scaling exponent for $q = 2$ is connected to the scaling of the autocorrelation function of the increments. Hence, the estimated generalized Hurst exponent $H(2)$ is comparable with the estimated H of R/S.

GHE combines sensitivity to any type of dependence in the data and simple algorithm. Besides, it is less sensitive to outliers than the R/S analysis, which relies on maxima and minima (Di Matteo et al., 2005). Moreover, Barunik and Kristoufek (2010) questioned the behaviour of the Hurst exponent estimate for non-normal process with heavy tails since the returns of the financial markets are not normally distributed and are heavy-tailed. Comparing various methodologies; they show that R/S and GHE are robust to heavy tails in the underlying data whilst GHE provides the lowest variance and bias as well.

3.3. Data and Results

Data comes from the digital asset store Kaiko which offers tick-by-tick trade data for 6,000+ currency pairs across 32+ exchanges including Bitfinex, the world's leading cryptocurrency trading platform. We examine dollar-denominated data from Bitfinex exchange for 4 cryptocurrencies, choosing those with the highest market capitalization, namely Bitcoin, Ethereum, Ripple and Litecoin. More information on those cryptocurrency markets is provided in Table 3.1 below.

Table 3.1: Summary of the sample cryptocurrencies (as of 06.05.2019)

#	Name	Market Cap	Price	Circulating Supply	Data starts from
1	Bitcoin	\$101.019.023.292	\$5.712,11	17.685.062 BTC	01/04/13
2	Ethereum	\$17.060.582.832	\$161,02	105.951.478 ETH	09/03/16
3	XRP	\$12.601.538.021	\$0,299416	42.087.046.846 XRP	23/06/2018
4	Litecoin	\$4.506.090.567	\$73,09	61.647.458 LTC	19/05/13

Cryptocurrency Market Capitalization Data.

Source: <https://coinmarketcap.com/>

For each trade, the data includes a GMT timestamp, amount of cryptocurrency traded and the cryptocurrency price in terms of USD. For each interval, we use that interval's closing price (instead of the volume-weighted average price) to calculate log-returns, at six different interval lengths (i.e. 1, 5, 10, 15, 30, and 60 min). Returns are calculated by taking the difference in the logarithm of two consecutive prices. Sample data for the cryptocurrencies start from 01/04/13, 09/03/16, 10/08/17 and 19/05/13 for Bitcoin, Ethereum, Ripple and Litecoin, respectively. For all coins, the sample ends on 23/06/2018. After estimating the Hurst exponents using R/S, GHE and GPH methods, we take their differences from 0.5 to determine the deviation from the efficiency. Accordingly, the less the deviations from 0.5, the more efficient the cryptocurrency is. Figure 3.1 presents the evolution of informational efficiency of each cryptocurrency across different frequencies. The plots clearly show that the degree of efficiency changes from one frequency to another. The optimal sampling frequencies that maximize weak form market efficiency are reported in Table 3.2.

Table 3.2: Optimal sampling frequencies maximizing weak form market efficiency with respect to different techniques for estimating Hurst exponent

Cryptocurrency	R/S	GPH	GHE
BTC	10 m	5 m	5 m
ETH	30 m	10 m	10 m
XRP	5 m	5 m	10 m
LTC	10 m	30 m	10 m

Accordingly, we can achieve more efficiency with 5-min and 10-min frequencies than 1-min, 15- min or 60-min frequencies. More specifically, 5-min is mostly optimal for BTC and XRP whereas 10-min is optimal for ETH and LTC in our sample period. These results are consistent with these of Andersen (2000) who states that the 5-min

interval is the highest at which enough data is available to reflect the high-frequency behavior of the series while also at the same time enough observations free of noise problems are provided.

For each currency, the results show that neither 1-minute frequency nor 60-minute frequency is optimal in terms of efficiency. The efficiency is lower when we use 60-minute frequency rather than 5- or 10-minute frequency since a higher-frequency market enables investors to respond to new information and to adjust their asset holdings more quickly. On the other hand, 1-minute frequency data does not give more efficiency. Except the noise in the data, as a shortcoming, the high-frequency market gets 'thinner' and thus attracts less investors since they prefer not to trade expecting superior relative returns in future periods, which leads to low transaction volume and relative illiquidity. This trade-off, together with the timing of incoming information, results in the optimal trading frequency of 5- and 10- minute intervals. The test results also indicate that the degree of informational efficiency differs from one cryptocurrency to another. Figure 3.2 plot the evolution of efficiencies of four markets across different time intervals together.

The results of the R/S test show that LTC is the most efficient cryptocurrency for each frequency in our sample period. Moreover, the R/S test provide evidence that BTC is more efficient than XRP in 10-min data interval which is optimal frequency for both cryptocurrencies. Investors in the XRP market can generate more abnormal profits by implementing trading strategies, compared to BTC.

The results from GHE test reveal that 10-min is optimal frequency for all cryptocurrencies, except for BTC. BTC is the most inefficient cryptocurrency at the 10-min level of data whereas it is the most efficient at the 5-min sampling frequency (where the optimal frequency is attained for BTC). Not only GHE test, but the GPH test also validates the same fact that BTC is the most efficient cryptocurrency at 5-min sampling. However, the results of the GPH test provides evidence that ETH is most efficient one among these 4 cryptocurrencies at 10-min intervals. One possible explanation could be related to that ETH has the second-highest market capitalization and supports much more functionality than Bitcoin (Chen et al., 2017). Moreover, according to the GPH method, XRP is more inefficient than LTC and ETH at 30-min data sampling.

To characterize the impact of frequency on the efficiency better, we consider Spearman correlations between the efficiency rankings within the same methodology but across different frequencies. Spearman's rank-order correlation allows us to evaluate the association between variables that are measured at the ordinal level. The averages of Spearman correlation coefficients in Table 3.3 are 0.43, 0.29 and 0 for R/S, GPH and GHE methods, respectively. The low correlations suggest that there is no significant linear relationship between those 6 different frequencies. Put it differently, the efficiency in cryptocurrency market varies across frequencies so the frequency matters.

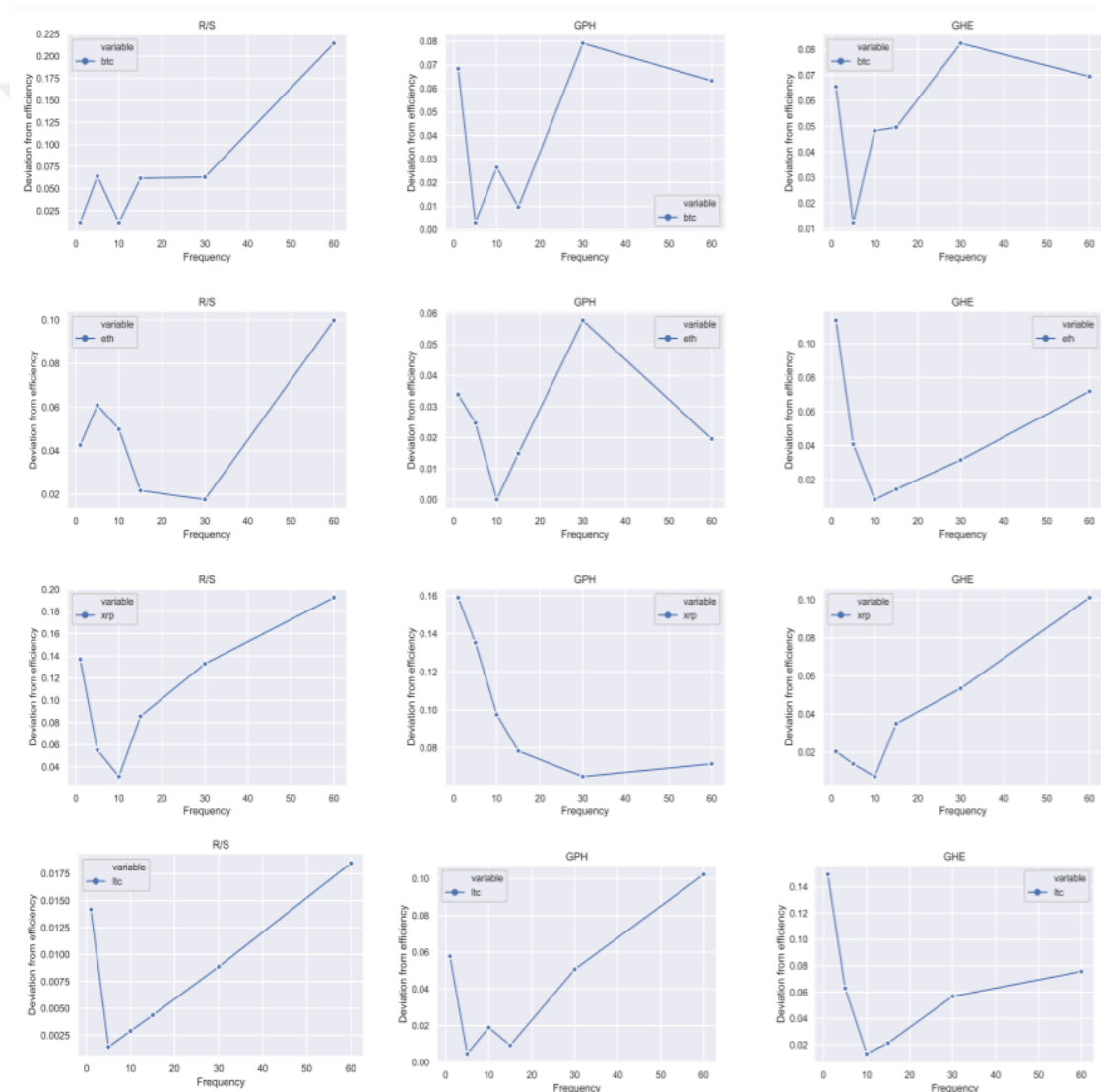


Figure 3.1: The evolution of informal efficiency of each cryptocurrency across different frequencies with three techniques

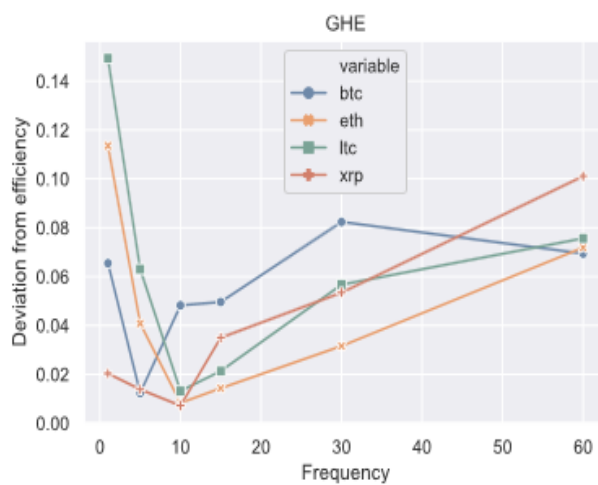
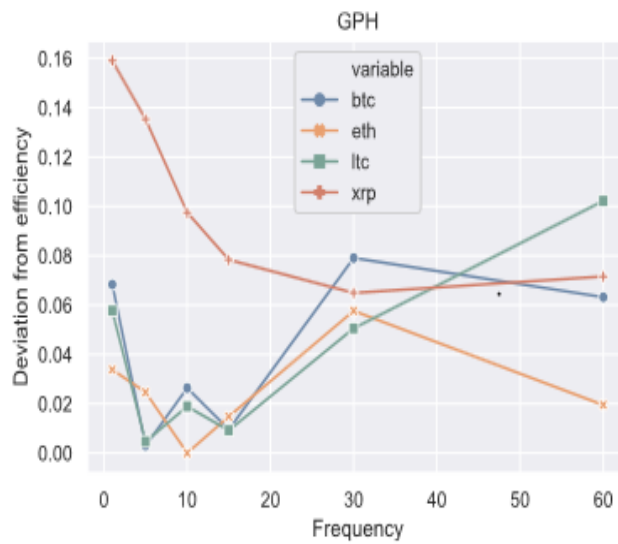
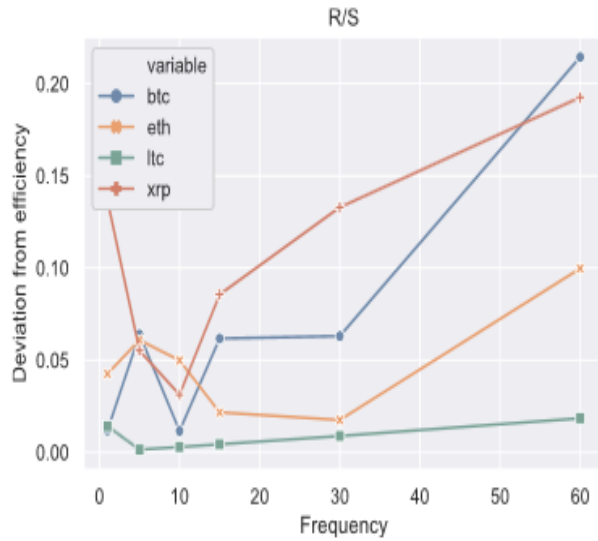


Figure 3.2: The evolution of informational efficiency of four cryptocurrency across different frequencies with three techniques

Table 3.3: Spearman correlation coefficients between sampling frequencies for different Hurst exponent estimation techniques

R/S	1m	5m	10m	15m	30m	60m
1m	1.0	-0.4	0.6	0.4	0.4	-0.2
5m	-0.4	1.0	0.4	0.4	0.4	0.8
10m	0.6	0.4	1.0	0.4	0.4	0.2
15m	0.4	0.4	0.4	1.0	1.0	0.8
30m	0.4	0.4	0.4	1.0	1.0	0.8
60m	-0.2	0.8	0.2	0.8	0.8	1.0

GPH	1m	5m	10m	15m	30m	60m
1m	1.0	0.2	1.0	0.4	0.6	0.4
5m	0.2	1.0	0.2	0.8	-0.2	0.0
10m	1.0	0.2	1.0	0.4	0.6	0.4
15m	0.4	0.8	0.4	1.0	0.4	-0.4
30m	0.6	-0.2	0.6	0.4	1.0	-0.4
60m	0.4	0.0	0.4	-0.4	-0.4	1.0

GHE	1m	5m	10m	15m	30m	60m
1m	1.0	0.8	0.4	-0.6	0.0	-0.2
5m	0.8	1.0	-0.2	-0.8	-0.4	0.4
10m	0.4	-0.2	1.0	0.4	0.8	-0.8
15m	-0.6	-0.8	0.4	1.0	0.8	-0.2
30m	0.0	-0.4	0.8	0.8	1.0	-0.4
60m	-0.2	0.4	-0.8	-0.2	-0.4	1.0

3.4. Conclusion

This study contributes to the debate surrounding the market efficiency of cryptocurrencies using intraday data at six different frequencies (1, 5, 10, 15, 30 and 60 min). We examine the frequency tie with the efficiency in four main cryptocurrency markets (Bitcoin, Ethereum, Ripple and Litecoin) using Hurst exponents estimated by various techniques. The analysis shows major discrepancies on the predictability of cryptocurrency returns for alternative frequency intervals. More specifically, the outcomes provide strong evidence on weak-form informational efficiency for 5m and 10m series whilst informationally inefficiency for 1, 15 and 60 minutely returns, hence market efficiency displaying a U-shaped pattern with respect to sampling frequency. These findings provide a guide for investors and policy makers. In particular, high-frequency traders who use algorithmic trading strategies can generate abnormal profits in the selected cryptocurrencies by trading on 1-minute or 60-minute basis. On the other hand, sophisticated traders placing orders within 5- or 10-minute scales are less likely to beat the market. In addition to this, to protect unsophisticated traders and to prevent adverse consequences of long memory patterns on them, financial market regulators may consider analyzing these markets at different frequencies and introduce regulations to improve efficiency levels.

Further research can focus on (i) whether these findings are stylized facts for only cryptocurrencies or are they valid for other asset classes as well; and (ii) if the same efficiency-frequency nexus holds for Bitcoin futures just as the Bitcoin spot market.

CHAPTER IV

HIGH-FREQUENCY ASYMMETRIC VOLATILITY CONNECTEDNESS BETWEEN BITCOIN AND MAJOR PRECIOUS METAL MARKETS

4.1. Introduction

The last decade was marked by increasing integration of international markets, which has resulted in crashes and financial crises, including the global financial crisis in 2008 and the European debt crisis in 2012. The increase in cross-market linkages or spillovers has increased portfolio riskiness and decreased diversification benefits, pushing investors and portfolio managers to find alternative assets that help to hedge exposure risk. Precious metals, particularly gold, palladium, platinum, and silver, constitute good alternatives for hedging because of their low correlation with other financial and commodity assets (such as stocks, currency bonds, and oil markets) and the safe-haven asset characteristics that they may provide in periods of financial turmoil (Baur and Lucey, 2010; Baur and McDermott, 2010; Jensen et al., 2002; Draper et al., 2006; Canover et al., 2009; Reboredo and Rivera-Castro, 2014).

As with precious metals, Bitcoin (BTC) has proven to be resilient during times of distress, ever since it was created in 2009, accentuating its potential role as a hedge and safe haven for financial and commodity markets against rising global uncertainty (Dyhrberg, 2016; Bouri et al., 2017b, 2017c; Corbet et al., 2018; Bouoiyour et al., 2018, Selmi et al., 2018).

BTC is based on a decentralized peer-to-peer network known as Blockchain. It is an unregulated digital currency derived from online mathematical cryptography and recently perceived as a substitute for government-backed currencies. Being one of the most popular cryptocurrencies—now perceived as a new type of financial asset—as well as the largest one, BTC has grown exponentially in value along with the media interest in the phenomenon and the attention it has received in the finance literature.⁵ The literature has considered BTC from different perspectives. While a small group of studies such as Dwyer (2015), Bariviera (2017), and Bariviera et al. (2018) examine the technical aspects and stylized facts of BTC, most of the studies focus on whether BTC prices satisfy either the weak or semi-strong forms of the efficient market hypothesis (e.g., Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017). Another growing strand of literature specifically considers BTC's return-volatility characteristics (Bouri et al., 2017a; Peng et al., 2018) and whether speculative bubbles occur in the BTC market (Cheah and Fry, 2015; Corbet et al., 2018). Other studies point out that BTC is viewed as a speculative investment rather than a safe haven or a hedge (Kristoufek, 2013; Yermack, 2014; Molnár et al., 2015; Ciaian et al., 2016) while some works show that this may not necessarily be the case. BTC could be plausibly included in optimal portfolios since it enjoys trust when an economic crisis occurs or when mainstream currencies and assets lose their credibility (Eisl et al., 2015; Popper, 2015; Gangwal, 2016; Baur et al., 2018).

Despite growing research on the hedge and safe-haven properties of BTC vis-à-vis major world stock indices, bonds, oil, gold, and the general commodity index, the relationships between BTC and precious metals except gold have so far been ignored. To enrich the related empirical literature, this paper investigates the linkages between BTC and major precious metal markets and its role as a hedge and/or safe haven to protect against similar risks, using five-minute frequency data and the methods developed by Diebold and Yilmaz (2014) and Baruník et al. (2017).

⁵ The BTC market is open 24 hours a day and 7 days a week and is rather young. However, with a market capitalization of more than \$112 billion and a market share of more than 53.8% in the cryptocurrency world as of October 2018, the role of BTC can no longer be ignored in the financial markets. Futures contracts on BTC have begun to be traded on the Chicago Board Options Exchange (CBOE) as of December 10, 2017, indicating that BTC is now a valid financial asset not only in the eyes of traders, but also policy makers. With these contracts, investors now participate in a regulated marketplace when trading by taking their perceptions of BTC prices into account. The latest move by CBOE has taken the role of BTC in financial markets to a whole new level.

Our findings can be summarized as follows: (i) We find significant volatility spillover effects among precious metals and BTC. (ii) Moreover, the spillover trend intensified during general periods of slowdown in global economic activity as well as the Brexit vote and the US presidential election, evidencing financial contagion. In terms of net spillovers, palladium is the largest net contributor of spillovers, followed by gold; BTC is a net recipient of spillovers. Evidence of asymmetry in semi-volatility transmission shows that BTC heavily transmits net positive spillovers to other assets. The bad volatility of palladium affects the volatility of other assets more than its good volatility does. On the other hand, the extent of the net spillover of gold is time dependent. We also identify the network of connectedness and posit that palladium has the greatest influence on the good and bad volatility of BTC. Our findings are in line with existing evidence that Bitcoin is a valuable portfolio diversifier (Bouri et al., 2017b; Bouri et al., 2017c; Brière et al., 2015; Corbet et al., 2018; Dyhrberg, 2016; Guesmi et al., 2019), which we have extended by considering asymmetric connectedness between positive- and negative-volatility spillovers.

This study adds to the existing literature in four ways. First, it investigates the asymmetric relations between BTC and precious metals such as gold, silver, platinum, and palladium. This analysis would assist investors to determine whether BTC provides a viable alternative to all types of precious metals as a hedger/diversifier. In addition, it would help policy makers and regulatory bodies perceive the role of this digital currency as an investment asset compared to precious metals. Second, instead of using daily data, as most of the previous studies did, we get to the high-frequency level and analyze the relationship between BTC and precious metals at intervals of five minutes. The idea is that algorithmic (especially high-frequency) trading has dominated the trading scene in recent years. In this structure, automated computers are programmed to make rapid decisions in reaction to varying market data in real time (Sensoy, 2018). As of 2012, algorithmic trading constituted 85% of the total trading volume in US equities, with high-frequency trading strategies (maintaining a long position in an asset for merely a few minutes) representing a big part of this value (Glantz and Kissell, 2013). Today, algorithmic trading platforms for customers are propelled by several BTC exchanges, requiring an analysis of the relationship between BTC and other assets at the intraday level. However, only a few studies have so far analyzed the BTC market using high-

frequency data (Bariviera et al., 2018; Peng et al., 2018). To the best of our knowledge, no previous study has conducted this type of analysis.

Third, the study analyzes daily intraday data for a four-year period that includes both slowdowns in global economic activity and upward trends in growth rates of advanced economies. The sample period also includes crucial events such as the UK's exit from the EU (Brexit) and the US presidential election, which led to uncertainty over the global growth outlook. Such events help us to analyze the dynamics of equicorrelations and volatility spillovers as well as design optimal portfolios and hedging strategies during periods of global economic and political uncertainty. Finally, we apply state-of-the-art methodologies in our analysis, such as Diebold and Yilmaz's (2012) generalized spillover index and directional spillover measure, Baruník et al.'s (2017) methodology for measuring directional spillover asymmetry, and Diebold and Yilmaz's (2014, 2016) methodology for the network topology of market connectedness. The time-varying total volatility spillover index between BTC and precious metals, obtained using dynamic rolling-sample analysis, provides useful information on the behavior of volatilities over time. Further, the exploration of the dynamics in the pattern of directional asymmetries helps us see the effect of positive or negative shocks on volatility spillovers.

The remainder of the study is organized as follows. Section 2 reviews the related literature. Section 3 describes the methodology used in this study. Section 4 presents the data and the descriptive statistics. Section 5 discusses the results and their implications for portfolio risk management. Section 6 concludes the paper.

4.2. Literature review

A growing corpus of literature has addressed the spillover effect between financial markets. Information regarding the spillover effect is of particular importance for asset allocations and risk management. Further, the interdependence and contagion among the financial markets provide useful information for rescue measures and is therefore crucial for regulatory authorities and international financial institutions (Shahzad et al., 2018). Extant empirical studies show, by providing useful insight regarding the relationship between gold and the stock and bond indices of numerous

developed countries, that gold is a safe haven for international stock and bond markets (Baur and Lucey, 2010; Baur and McDermott, 2010; Coudert and Raymond, 2011, O'Connor, 2015; Yaya, 2016; Ji et al., 2018a). The role of other precious metals is rarely documented despite their capacity to effectively hedge investment portfolios.

However, more recent studies, including Lucey and Li (2015), Batten et al. (2015), and Agyei-Ampomah et al. (2014), emphasize the resilience of the silver, platinum, and palladium markets (along with gold markets) to financial crises and suggest that adding precious metals to a portfolio can lower the systematic risk of investment through diversification, particularly during periods of abnormal equity market volatility (Hillier et al., 2006; Belousova and Dorfleitner, 2012; Skiadopoulos, 2012; Lucey and Li, 2015).

Mensi et al. (2017) investigate the time-varying risk spillovers between precious metals and the US, Japanese, European, and Asian stock markets based on the spillover index of Diebold and Yilmaz (2012). They find evidence of spillover effects between the precious metal and stock markets. In addition, they show that all the aforementioned stock markets (except the Japanese market) were key determinants of risk spillovers and the four precious metals markets were net receivers of risk during the global financial crisis and European sovereign debt crisis periods.

Several studies focus on the spillover effects from precious metals to currency and crude oil prices. Antonakakis and Kizys (2015) find, by investigating the dynamic interdependence among returns and the volatility of commodities and currency markets, that the information contents of gold, silver, platinum, and the CHF/USD and GBP/USD exchange rates are the source of returns and volatilities of palladium, crude oil, and the EUR/CHF and GBP/USD exchange rates. In addition, they show that gold and CHF/USD are the leading commodity and currency transmitters, respectively, of return and volatility spillovers to the other assets in their model. Lastly, they note that the results of the dynamic spillover analysis are time- and event-dependent. Similarly, Fernandes-Perez et al. (2017) investigate the contemporaneous spillovers among precious metals (gold, silver, platinum, and palladium), crude oil, and US exchange rates using a structural vector autoregressive (VAR) model. The authors show strong and asymmetric contemporaneous spillovers

that are not captured by Granger causality statistics. Hammoudeh and Yuan (2008) also examine a relationship in the form of integrated networks. They analyze the US precious metals market using generalized autoregressive conditional heteroskedasticity (GARCH) models and find that lagged oil prices serve as a determinant of the univariate volatilities of silver, gold, and copper. Huang et al. (2012) analyze the effect of the US dollar and oil prices on the Chinese precious metals market (copper, gold, and silver) using a VAR model. They find that the US dollar determines the prices of Chinese gold and silver. Recently, Shahzad et al. (2018a) investigate the spillover from international oil prices to a wide array of precious metal (gold, silver, platinum, palladium, and titanium) returns. Implementing the VAR for a value-at-risk (VaR) specification, they examine the upside/downside risk spillovers from oil to the precious metals markets and concurrently measure the response of each precious metal to the expected negative/positive oil shocks.

Another strand in the literature addresses the individual relationships between Bitcoin and other financial assets and highlights the valuable role of Bitcoin as an investment asset. Dyhrberg (2016), Bouri et al. (2017b), and Bouri et al. (2017c) emphasize the benefits of including BTC in portfolios. Dyhrberg (2016) examines the hedging capabilities of BTC with the asymmetric GARCH methodology using daily USD/EUR and USD/GBP exchange rates and the FTSE index for the period July 19, 2010 to May 22, 2015. The author finds that BTC can hedge against the FTSE index and—in the short term—the US dollar. In the same vein, Bouri et al. (2017b) explore the diversification, hedging, and safe-haven properties of BTC against major world stock indices, bonds, oil, gold, the general commodity index, and the US dollar index by means of a dynamic conditional correlation model. They show, using daily and weekly data, that BTC is appropriate for diversification purposes. However, BTC exhibits a strong safe-haven property in the case of weekly extreme downward movements in Asian stocks. Bouri et al. (2017c) also examine, by applying bivariate asymmetric dynamic conditional correlations (DCCs), whether BTC has adopted the role of a diversifier, hedge, or safe haven against both general commodity indices and specific energy commodity indices. Their findings suggest that BTC is considered a strong hedge and a safe haven against both commodity indices.

Bouoiyour and Selmi (2017), using an approach based on ensemble empirical mode decomposition, explore the hedging and safe-haven capabilities of BTC for the US stock price index. The results demonstrate that BTC's ability to act as a safe haven depends on time: it works as a weak safe haven in the short run and a hedge in the long run. Corbet et al. (2018) analyze the relationships between three cryptocurrencies (BTC, Ripple, and Litecoin) and a variety of other financial assets such as the MSC GSCI total returns index, the USD broad exchange rate, the SP500 index, the COMEX closing gold price, VIX, and the Markit ITTR110 index. They implement the generalized variance decomposition methodology to assess the connection between cryptocurrencies and the mainstream assets. Their findings indicate that cryptocurrencies are interconnected and may serve as a diversifier that benefits investors in the short term. Katsiampa (2018), while investigating the volatility dynamics of Bitcoin and Ether, exhibits evidence of interdependencies in the cryptocurrency market. In addition, the author shows that Ether can be an effective hedge against Bitcoin, while the analysis of optimal portfolio weights points out that Bitcoin should outweigh Ether. Similarly, Ji et al. (2019) employ a set of measures developed by Diebold and Yilmaz (2012, 2016) to observe connectedness via return and volatility spillovers across six large cryptocurrencies. Regarding volatility spillovers, the results show that Bitcoin has the greatest effect on other cryptocurrencies, followed by Litecoin; Dash exhibits extremely weak connectedness, offering hedging and diversification benefits in the cryptocurrency market. They further reveal that trading volume and global financial and uncertainty effects are determinants of spillovers. In addition, gold prices have a negative effect on net directional-volatility spillovers, whereas VIX shows a positive effect. In the same vein, Aslanidis et al. (2019) study cryptocurrencies and traditional assets (stock and bond indices, and gold). Applying dynamical conditional correlation analysis to the cryptocurrency market, they find positive correlations among cryptocurrencies and negligible correlations between cryptocurrencies and traditional financial assets. An investigation by Canh et al. (2019) is one of the recent studies that examine volatility spillovers in the cryptocurrency market. Analyzing the largest seven cryptocurrencies (Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bitcoin), they document volatility spillovers with strong positive correlations among cryptocurrencies and find limited diversification benefits within the cryptocurrency market. Ji et al. (2018b) question the causal relationships between Bitcoin and several financial assets (i.e.,

equities, bonds, currencies and commodities) using a directed acyclic graph-based approach and forecast error variance decompositions. Their results indicate that Bitcoin is quite isolated. However, they find evidence of lagged relationships between Bitcoin and some assets, especially during the bearish state of the Bitcoin market.

Bouoiyour et al. (2018) compare the roles of BTC and gold as a hedge, a safe haven, and/or a diversifier against extreme fluctuations in oil prices, using a quantile-on-quantile approach and the conditional VaR measure. The authors find that both BTC and gold reduce oil-related portfolio risks but BTC can serve as a more pronounced hedge and safe haven than gold. Similarly, Selmi et al. (2018) compare the hedging features of Bitcoin and gold against extreme oil price movements, under alternative distributions of both oil and Bitcoin/gold markets. By controlling for various uncertainty proxies, they confirm the usefulness of including both Bitcoin and gold, but not oil, in a portfolio risk management plan during political and economic turmoil. The diversification benefits of BTC are also supported by the recent work of Guesmi et al. (2019). Bouri et al. (2018a) examine daily dependence between global financial stress and Bitcoin by applying various standard and quantile-based copula models. The authors find evidence of directional predictability from the global financial stress index to Bitcoin returns, highlighting Bitcoin's ability to act as a safe-haven against global financial stress for approximately 60 days. Shahzad et al. (2019b) contribute to the debate surrounding the safe-haven property of Bitcoin proposing a new definition of a weak and strong safe haven within a bivariate cross-quantilogram approach. Their results show that Bitcoin, gold, and the commodity index are weak safe havens in some cases and that the safe-haven roles of those assets are time-varying.

Bouri et al. (2018b) study the nonlinear, asymmetric and quantile effects of aggregate commodity index and gold prices on the price of Bitcoin by implementing several advanced autoregressive distributed lag (ARDL) models. The authors suggest the possibility to predict Bitcoin price movements based on price information from commodity and gold prices.

Anyfantaki et al. (2018) assess other cryptocurrencies (Ether, Ripple, and Litecoin), in addition to Bitcoin, in terms of their diversification benefits. They apply stochastic dominance spanning tests with in-sample and out-of-sample data and find that

cryptocurrencies provide investment opportunities for risk-averse investors to look beyond traditional asset classes (stocks, bonds, and cash). In their analysis, cryptocurrency markets are segmented from traditional stock and bond markets to explain the domination of the expanded investment universe.

Despite emerging studies on the hedge and safe-haven properties of BTC, their asymmetric interlinkages to precious metals (such as gold, silver, platinum, and palladium) remain uncharted.

4.3. Econometric Modeling Framework

4.3.1. Asymmetric Volatility Spillovers

We introduce a new measure of volatility to assess asymmetries due to negative and positive shocks. Let us assume that the intraday return r_t is the log difference return of the five-minute price, i.e., $r_t = 100 \times (\log P_t - \log P_{t-1})$, such that the realized variance (RV) can be defined as

$$RV = \sum_{i=1}^n r_i^2 \quad (4.1)$$

Following Barndorff-Nielsen et al. (2010), we decompose RV into estimators of realized semivariance (RS) to measure asymmetry due to negative or positive movements in specific volatilities (e.g., bad and good volatility).⁶ The negative and positive realized semi-variances (RS^- and RS^+) are defined as follows:

$$RS^- = \sum_{k=1}^n r_k^2 |r_k < 0| \quad (4.2)$$

$$RS^+ = \sum_{k=1}^n r_k^2 |r_k \geq 0| \quad (4.3)$$

The summation of negative realized semi-variance, a measure of downside risk (RS^-), and positive realized semi-variance, a measure of upside risk (RS^+), is always equal to the total realized variance RV (i.e., $RV = RS^+ + RS^-$). Thus, the realized

⁶ Earlier studies concluded that the realized volatility provides consistent estimates of integrated volatility rather than the proxy of volatility, i.e., absolute returns (Andersen and Bollerslev, 1998; Andersen et al., 2001, 2003; Barndorff-Nielsen and Shephard, 2002).

semi-variances provide a full picture of the realized variance.

To account for the intensity of good and bad volatility, this study distinguishes between the negative semi-variance $R_t^- = (R_{it}^-, \dots, R_{nt}^-)'$ and the positive semi-variance $RS_t^+ = (RS_{it}^+, \dots, R_{nt}^+)'$ in the total volatility spillovers, denoted by $RV_t = (RV_{it}, \dots, RV_{nt})'$. To this end, we adopt the Diebold and Yilmaz (2012) methodology, which follows directly from the variance decomposition associated with an N-variable vector autoregression fitted to volatility. An N-dimensional vector of realized variance, $RV_t = (RV_{it}, \dots, RV_{nt})'$ in N different markets, is defined as a covariance stationary VAR(p):

$$RV_t = \sum_{i=1}^p \Psi_i RV_{t-i} + \varepsilon_t \quad (4.4)$$

where Ψ_i are $N \times N$ autoregressive coefficient matrices and ε_t is a vector of error terms that are assumed to be serially uncorrelated. As the above VAR process is assumed to be covariance stationary, a moving average representation can be written as $RV_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices Θ_j are obtained from the recursion $\Theta_i = \sum_{j=1}^p \Psi_j \Theta_{i-j}$, with $\Theta_0 = I_N$ and $\Theta_i = 0$ for $i < 0$.

To estimate the asymmetric volatility spillovers, we construct a VAR model (Eq.(4.4)), but replace the vector of volatilities $RV_t = (RV_{it}, \dots, RV_{nt})'$ with a $2N$ dimensional vector of negative and positive semi-variances $RS_t = (R_{it}^+, \dots, R_{nt}^+, RS_{it}^-, \dots, R_{nt}^-)'$. The elements of the $2N \times 2NH$ -step-ahead generalized forecast error variance then has the form

$$\tilde{c}_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma \Theta_h' e_i)}, \quad i, j = 1, \dots, 2N \quad (4.5)$$

where the covariance matrix of errors in the non-orthogonalized VAR is represented by Σ . σ_{jj} denotes the standard deviation of the error term of the j^{th} equation, and e_i is a $2N \times 1$ vector, which takes one as the i^{th} element, and zero otherwise. Finally, Θ_h is the coefficient matrix, which multiplies the h -lagged error in the infinite moving-average representation of non-orthogonalized VAR.

4.3.2. Directional Spillover Asymmetry Measure

To quantify the asymmetry volatility spillover, we apply realized semi-variances to

obtain more accurate information about spillover behavior by defining a directional spillover asymmetry measure. The asymmetry is the difference between the directional volatility spillover coming from a positive or negative semi-variance. Unlike the symmetric directional spillovers in realized volatilities, we consider the elements of the H -step-ahead generalized forecast error variance decomposition in Eq. (4.5) to compute asymmetric directional spillovers. We define directional spillover from market i to all other markets j as

$$S_{2N,i \rightarrow *}(H) = \frac{1}{2N} \sum_{\substack{i=1, i \neq j \\ |i-j| \neq N}}^{2N} \tilde{c}_{j,i}^g \times 100, \quad i, j = 1, \dots, 2N \quad (4.6)$$

Based on the directional spillovers in Eq. (4.3), we conjecture the asymmetric directional spillovers that determine how the bad- and good-volatility shocks on one market affect the volatility in all other markets. Following Baruník et al. (2017), the net directional asymmetry spillover (SAM) is defined as the difference in the response of all other markets to a bad- or good-volatility shock in market i as follows:

$$SAM_{2N,i \rightarrow *}(H) = S_{2N,i \rightarrow *}(H) - S_{2N,(i+N) \rightarrow *}(H), \quad i, j = 1, \dots, N \quad (4.7)$$

where $S_{2N,i \rightarrow *}$ and $S_{2N,(i+N) \rightarrow *}$ are volatility spillover indices due to positive and negative semi-variances, respectively, using H -step-ahead forecasting at time t . If the $SAM_{2N,j \rightarrow *}(H)$ is negative (positive), we observe a strong effect of bad (good) volatility from market i to all other markets j . We also use a moving window of 100 days to include the time-varying asymmetric behavior of the volatility spillover.

4.3.3. Spillover Asymmetry Measure

To further quantify the magnitude of asymmetric volatility spillovers, we define a spillover asymmetry measure ($SAM_{2N}(H)$) as follows:

$$SAM_{2N}(H) = \sum_{i=1}^N S_{2N,i \rightarrow *}(H) - \sum_{i=N+1}^{2N} S_{2N,(i+N) \rightarrow *}(H) \quad (4.8)$$

The magnitude of $SAM_{2N}(H)$ indicates the degree of asymmetry in spillover due to RS_t^- and RS_t^+ . When the bad (good) volatility of RS_t^- (RS_t^+) dominates the good (bad) volatility of RS_t^+ (RS_t^-), $SAM_{2N}(H)$ is negative (positive). However, if the spillover from RS_t^- and RS_t^+ are equal, $SAM_{2N}(H)$ takes a value of zero, which indicates that there is no spillover symmetry. To test the null hypothesis of symmetric connectedness ($SAM_{2N}(H) = 0$), we use the bootstrap confidence approach of

Baruník et al. (2016).

4.3.4. Network Connectedness in Asymmetry Volatility

Diebold and Yilmaz (2014, 2016) propose a network topology of all market connectedness and illustrate the variance decomposition matrix as the adjacency matrix of a weighted directed network. The elements of the adjacency matrix represent our pairwise directional connectedness, $S_{2N,i \leftarrow j}(H)$. The sum of the rows (node in degrees) is the total directional connectedness “From,” $S_{2N,i \leftarrow *}(H)$; and the sum of the columns (node out-degrees) is the total directional connectedness “To,” $S_{2N,i \rightarrow *}(H)$.

4.4. Data and Preliminary Analysis

In our analysis, we examine volatility spillover and its asymmetries between BTC and four major precious metals (gold, silver, palladium, and platinum). In this context, we generate daily realized semi-volatility based on high-frequency five-minute returns over the period January 15, 2014 to February 2, 2018. With the availability of high-frequency data, recent studies use five-minute high-frequency data for estimating realized volatility to eliminate the trade-off between accuracy and market microstructure noise (due to the bid-ask bounce, asynchronous trading, infrequent trading, and price discreteness) (Kumar, 2017; Bissoondoyal-Bheenick, et al., 2019; Horpestad, et al., 2019; Luo and Wang, 2019; Xu et al., 2019).

Note that positive (negative) returns are associated with good (bad) news of Bitcoin and the four precious metals. Each sample has 978 daily realized volatility for the sample period, with 234,306 observations of 5-min interval data available for the analysis. The tick data were obtained from Tick Data, Inc. In order to prevent estimation bias that may be caused by low trading activity on the market, we exclude weekends and holidays, as well as the periods December 24 to 26 and December 21 to January 2.

Figure 4.1 shows the dynamics of daily realized volatility from 2014 to 2018. We observe that, for daily realized volatility, major peaks emerge in the 2015–2016 sub-

period. The peaks result from irrational responses on the part of investors (e.g., panic and herd behavior). Investor reactions were strong following both good and bad news.

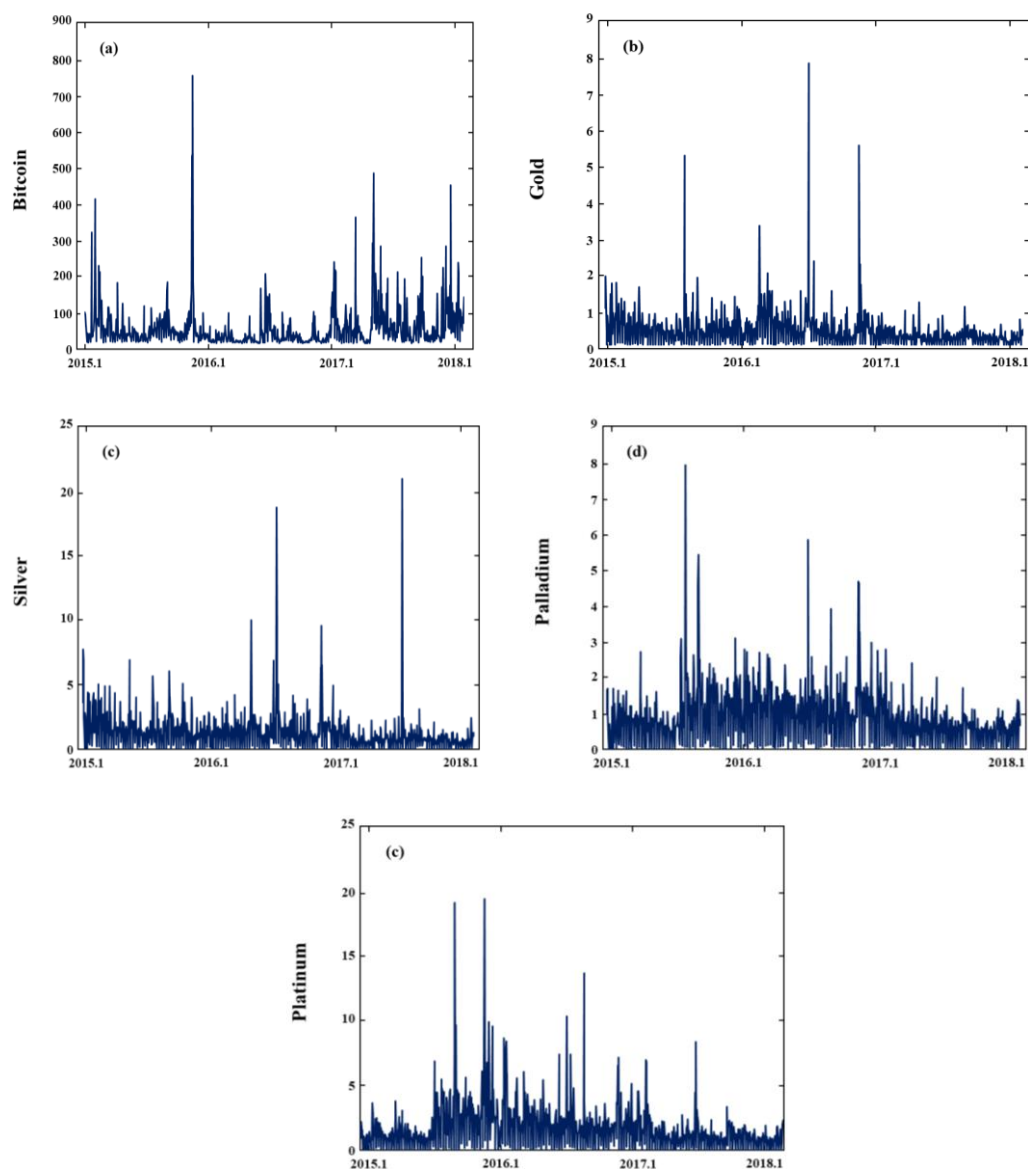


Figure 4.1: Dynamics of daily realized volatility

Note: This figure shows the realized variances of five assets obtained from five-minute intraday returns. Volatility is computed according to Eq. (4.1).

Table 4.1 presents the descriptive statistics for the estimated realized variances, upside semi-volatility, and downside semi-volatility. Panel A shows that BTC has the highest mean, as well as the highest standard deviation, of realized variance. The distributions of realized measures for all series exhibit positive skewness, which

means that most of the values are lower than the mean. For all distributions of realized measures, the kurtoses were substantially different from 3, which is the kurtosis of a univariate normal distribution, indicating high peaks and fat tails (leptokurtic). Therefore, based on these two statistical measures, we can conclude that none of the distributions of realized measures is normally distributed, which is also confirmed by the Jarque-Bera statistics. The difference between the means in Panels B and C is negligible, so we may conclude that both types of semi-volatility contribute equally to the realized variance.

Table 4.1: Descriptive statistics for realized volatility, upside semi-volatility, and downside semi-volatility

	Bitcoin	Gold	Silver	Palladium	Platinum
Panel A: Daily $\sqrt{RV}$					
Mean	5.650	0.579	1.034	0.895	1.199
St.dev.	3.343	0.287	0.507	0.383	0.597
Minimum	0.743	0.057	0.088	0.069	0.060
Maximum	27.651	2.821	4.614	2.855	4.465
Skewness	1.724	1.203	0.977	0.002	0.601
Kurtosis	8.142	9.384	7.796	4.020	5.050
Jarque-Bera	1562***	1897***	1093***	42***	230***
Panel B: Daily $\sqrt{RS^+}$					
Mean	3.932	0.405	0.720	0.626	0.840
St.dev.	2.428	0.214	0.363	0.282	0.439
Minimum	0.340	0.017	0.034	0.026	0.000
Maximum	20.100	2.296	2.857	1.828	3.201
Skewness	1.774	1.439	0.755	0.041	0.752
Kurtosis	8.477	11.018	5.306	3.566	5.340
Jarque-Bera	1735***	2957***	309***	13***	299***
Panel C: Daily $\sqrt{RS^-}$					
Mean	3.950	0.403	0.724	0.628	0.843
St.dev.	2.478	0.214	0.390	0.284	0.434
Minimum	0.149	0.008	0.040	0.020	0.006
Maximum	18.989	2.082	3.813	2.382	3.537
Skewness	1.789	1.282	1.421	0.238	0.730
Kurtosis	8.453	9.134	10.215	4.835	5.791
Jarque-Bera	1733***	1801***	2451***	146***	383***

Note: This table presents the descriptive statistics of realized volatility and semi-volatility over the sample period, December 15, 2014 to February 2, 2018. The Jarque-Bera statistic tests are for the null hypothesis of normality for the distribution of the series. *** indicates rejection of the null hypothesis at the 1 % significance level.

4.5. Empirical Analysis

This section presents and discusses the estimated results of the volatility spillover effect between the BTC and precious metals markets. The empirical results are divided into three subsections. In the first subsection, we estimate the dynamic spillovers and show the important property of volatility spillover between the BTC and precious metals markets. Second, we examine the asymmetry in semi-volatility transmission by capturing the asymmetric behavior of investors in relation to downside and upside risk. The last section explores the connectedness network to determine the net transmitter or net recipient of asymmetric volatility.

4.5.1 Dynamic of Volatility Spillover: Statistical Analysis

The total and net realized volatility spillover index between BTC and precious metals markets are reported in Table 4.2. The lower-right corner shows that the total spillover reaches 56.6%, implying a high level of volatility spillover between BTC and precious metals markets. More precisely, across our entire sample, 56.6% of the volatility forecast error variance in all five markets comes from spillovers. As regards the directional spillovers transmitted “To,” palladium is the highest contributor to other markets (80.9%), followed by gold (68.6%), silver (65.1%), and platinum (61.9%). The result indicates that palladium is the market that investors should be cautious of since it is the main source of volatility spillover shock to other precious metals. Both silver and platinum are neutral in terms of spillover contribution, with zero net values. Interestingly, BTC contributes only 6.4% of volatility spillover to precious metals markets and receives 20.4% of its volatility spillover from its counterpart market. In terms of net spillovers (“To”–“From”), palladium is the largest net contributor of spillovers (11.9%), followed by gold (2.9%), while BTC is the largest net recipient of spillovers (–14%). This result indicates that BTC has a much lower impact than precious metals. In fact, it contributes only 1.09% and 1.33% to the forecast error variance of gold and silver, respectively, whereas gold contributes 22.95% to that of silver. This result indicates that silver and palladium act as price discovery tools for gold. On the other hand, BTC provides greater diversification benefits than precious metals.

These findings accord with the results of the spillover tests of Corbet et al. (2018), albeit with different sample periods and data frequencies. Their analysis based on Diebold and Yilmaz's (2012) generalized variance decomposition methodology reveals little connectedness between cryptocurrency markets (Bitcoin along with Litecoin and Ripple) and other financial markets (e.g., gold, bond FX, SP 500, VIX, and GSCI). Their findings suggest—as does this paper, too—that Bitcoin can be an effective portfolio diversifier and offer safe haven properties for investors.

Table 4.2: Total spillovers in daily realized volatility

	Bitcoin	Gold	Silver	Palladium	Platinum	From
Bitcoin	79.62	4.99	4.26	6.27	4.85	20.4
Gold	1.09	34.26	22.33	25.08	17.24	65.7
Silver	1.33	22.95	34.99	23.75	16.98	65
Palladium	1.87	23.03	21.31	30.98	22.81	69
Platinum	2.08	17.59	17.16	25.77	37.4	62.6
To	6.4	68.6	65.1	80.9	61.9	282.8
All	86	102.8	100	111.9	99.3	Total:
Net	-14	2.9	0.1	11.9	-0.7	56.60%
Conclusion	Net-recipient	Net-contributor	Neutral	Net-contributor	Neutral	

Note: As determined by the Schwarz information criterion, the underlying variance decomposition is based on a daily VAR of order 4, identified using a generalized VAR spillover framework.

4.5.2 Dynamics of Volatility Spillover: A Graphical Analysis

Although the full-sample spillover tables and indexes provide a useful summary of “average” behavior, they do not show the changes taking place during our sample period. Figure 4.2 plots the time-varying total volatility spillover index between BTC and precious metals, obtained using a dynamic rolling-sample analysis. The graphical evidence illustrates that volatility spillovers vary greatly over time and respond to economic events. Volatility spillovers attained their maximum levels in the 2nd and 4th quarters of 2015. These periods correspond to a slowdown in global economic activity, which was caused by the downturn in emerging economies coupled with the subdued growth in advanced economies and the oil price plunge. The contraction in the Chinese economy as well as the slowdown in the Russian and Brazilian economies accounted for the downward pressure on the global growth rate. Furthermore, among the emerging economies, Eastern Europe and Latin America experienced almost zero growth rates. Among the advanced economies, the ongoing

recession in Japan had a substantial impact on the deceleration of the global growth rate.

As time passed, the total volatility spillover index recorded a significant downward movement beginning in 2016, which is most likely related to the monetary policies of advanced economies due to the deteriorated global growth prospects in 2015. The Bank of Japan preferred a negative policy rate while the European Central Bank announced a strong monetary easing program followed by a policy rate cut. In line with these, the Federal Reserve Board sent signals to the market about its mild monetary tightening. Accordingly, expectations of lower policy rates in advanced economies in the long run might be connected to the increase in risk appetite and decrease in risk premiums of emerging economies, which paved the way for capital flows towards emerging economies in the first quarter of 2016. Similarly, low levels of total volatility spillover were experienced in the third quarter of 2016, chiefly because of global economic growth. Among the advanced economies, the US, the Euro area, the UK, and Japan recorded upward trends in growth rates, with the US and the UK economies growing at a significantly stronger pace than previous periods.

The high levels of total spillover in the last quarter of 2016 and the first quarter of 2017 reflect the fallout of two distinctive events that led to uncertainty over the global growth outlook. One is the Brexit, whose implications for the global economy were still unclear. At the same time, the result of the US presidential election led to great uncertainty about economic policy in the US. These two incidents, which led to some policy responses in other economies through spillover effects, determined the high level of total spillover in the last quarter of 2016 and the first quarter of 2017.

Volatility spillovers attained their minimum levels in the third quarter of 2017. The trend coincides with the increasing volume of global trade.

Although we report noteworthy findings on the relationship between the total volatility spillover and specific events (i.e., political and macroeconomic events), we do not address the causal character or direction of relationships in our analyses. Further work on causal modeling techniques could help verify whether economic outlook or political events have an impact on the volatility spillover. An investigation of the causal relationships between those variables is beyond the scope of this study, and is therefore left for future research.

In summary, the volatility spillover index increases and decreases over time. Our interpretation is that periods of financial distress trigger large volatility spillovers in BTC and precious metals markets. The results suggest that investors should modify their portfolio structures accordingly.



Figure 4.2: Total volatility spillover of five assets

Notes: The dynamics of total spillovers are calculated using rolling-sample analysis with 100-day rolling windows.

Figure 4.3 illustrates the time evolution of net volatility spillover for each market in addition to the time-varying rolling analysis of the total volatility spillover. A closer inspection of this figure shows that gold and palladium are net transmitters of risk whereas BTC is a net recipient of shocks from precious metals. Gold plays an important role in financial markets with flight-to-quality in times of market distress, is significantly used in central banks' international reserves, and is a store of value, whereas palladium is in strong demand by the automotive sector. Although BTC is often named “new gold,” this analysis shows that gold and BTC have different properties. This result may be explained by the small size of BTC market capitalization compared to gold. Both silver and platinum are spillover-neutral over time.

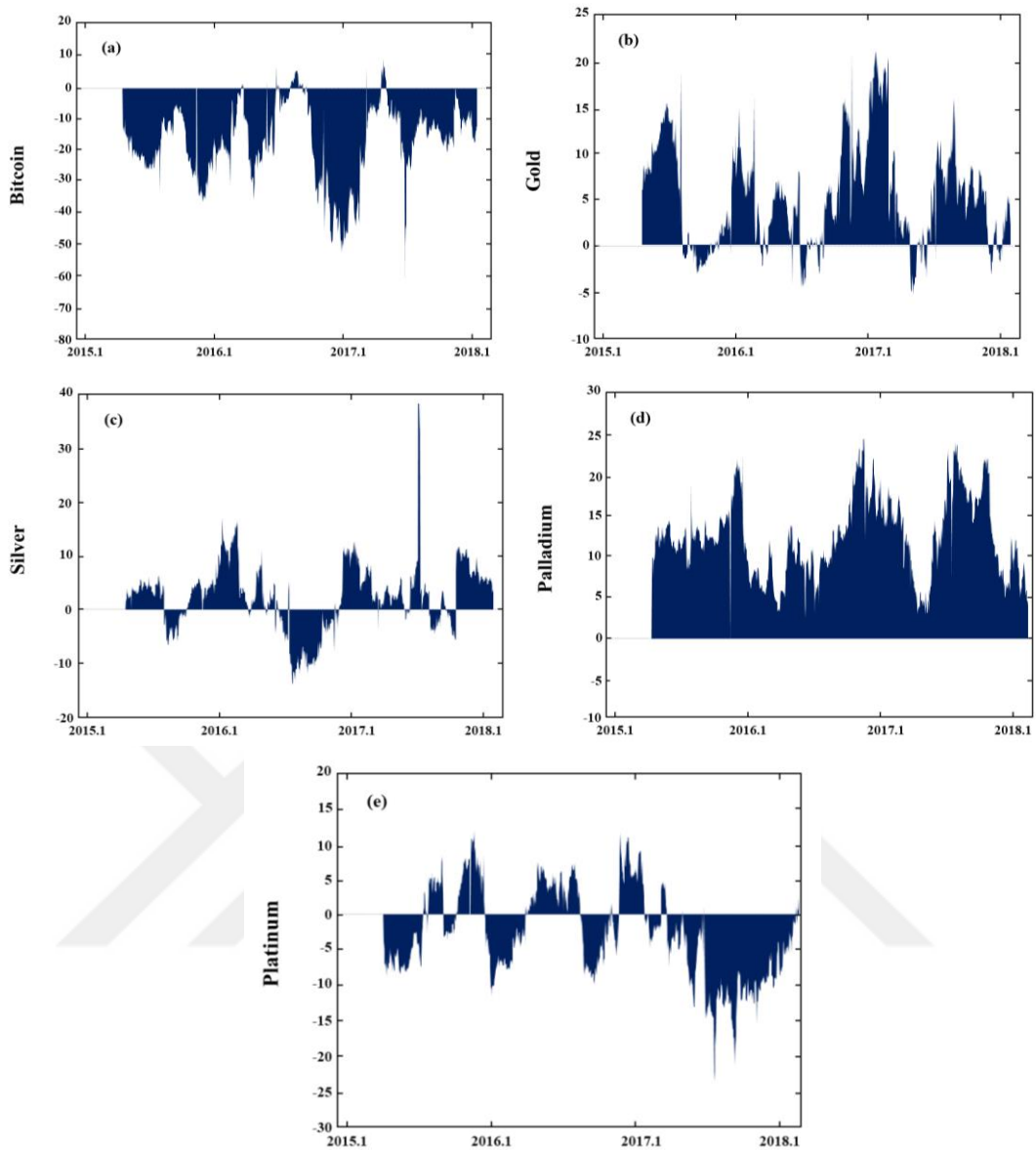


Figure 4.3: Net directional spillovers in daily realized volatility

Note: Positive values indicate that the asset is a volatility transmitter to other markets, whereas negative values indicate that the asset is a volatility recipient from other markets.

4.5.3 Asymmetries in Directional Volatility Spillovers

We now examine the asymmetric features of directional volatility spillovers between BTC and precious metals, taking into account the different magnitudes of volatility spillovers according to whether the shocks are positive or negative. Table 4.3 presents the information in a convenient matrix format, enabling us to distinguish the proportions in which good and bad volatilities from individual assets propagate across markets resulting in positive and negative spillovers that eventually translate into the

volatilities of the assets under research. The interpretations of the figures are the same as in Table 4.2; for this reason, we have not interpreted them here. Positive spillovers are the least-pronounced for BTC, which means that the spillovers of positive shocks transmitted from BTC to precious metals are relatively small. Differentiating between positive and negative shocks provides useful and complete information on volatility spillovers to generate more accurate inputs for portfolio risk management. Note that the spillover index is more pronounced for negative volatility, supporting the leverage effect hypothesis.

Table 4.4 shows how the asymmetries in directional volatility spillovers spread between BTC and precious metals. The results show that BTC (palladium) remains a net recipient (transmitter) of shocks from (to) other markets after accounting for good and bad volatilities. Gold has neutral effects for good volatilities, but is a net contributor of bad volatilities, suggesting asymmetry effects. This result also indicates the appropriateness of our methodology. The risk spillover of the platinum and palladium markets shifts according to whether the volatilities are good or bad.

Table 4.3: Asymmetric directional volatility spillover in semi-variances RS^+ and RS^-

		RS^+					RS^-					
		BTC	Gold	Silver	Palladium	Platinum	BTC	Gold	Silver	Palladium	Platinum	From
RS^+	BTC	48.07	3.03	2.75	3.48	2.48	27.93	2.91	2.44	3.73	3.18	51.9
	Gold	0.7	21.23	14.37	14.9	9.27	1.22	11.57	7.81	10.23	8.71	78.8
	Silver	0.85	13.98	20.98	13.82	9.22	1.29	8.98	12.12	10.29	8.46	79
	Palladium	1.12	13.05	12.52	18.44	12.29	1.8	9.33	8.37	12.34	10.74	81.6
	Platinum	1.19	9.17	9.52	14.06	22	1.85	7.81	7.26	11.41	15.73	78
RS^-	BTC	26.69	3.17	3.17	4.54	3.33	44.71	3.2	2.85	4.39	3.94	55.3
	Gold	0.57	11.29	9.15	10.46	7.57	1.01	21.29	13.59	15.32	9.74	78.7
	Silver	0.74	7.98	13	9.8	7.4	1.16	14.1	21.79	14.28	9.76	78.2
	Palladium	1.03	8.8	9.27	12.19	9.73	1.49	13.67	12.24	18.72	12.85	81.3
	Platinum	1.23	8.12	8.35	11.63	14.34	1.7	9.36	9.19	14.14	21.95	78.1
TO		34.1	78.6	82.1	94.9	75.6	39.4	80.9	75.9	96.1	83.1	740.8
ALL		82.2	99.8	103.1	113.3	97.6	84.2	102.2	97.7	114.9	105.1	Total: 74.10%

Table 4.4: Asymmetric pairwise directional volatility spillover in semi-variances RS^+ and RS^-

	RS^+					RS^-					
	BTC	Gold	Silver	Palladium	Platinum	BTC	Gold	Silver	Palladium	Platinum	
RS^+	BTC	0	2.33	1.9	2.36	1.29	1.24	2.34	1.7	2.7	1.92
	Gold	-2.33	0	0.39	1.85	0.1	-1.95	0.28	-0.17	1.43	0.59
	Silver	-1.9	-0.39	0	1.3	-0.3	-1.88	-0.17	-0.88	1.02	0.11
	Palladium	-2.36	-1.85	-1.3	0	-1.77	-2.74	-1.13	-1.43	0.15	-0.89
	Platinum	-1.29	-0.1	0.3	1.77	0	-1.48	0.24	-0.14	1.68	1.39
RS^-	BTC	-1.24	1.95	1.88	2.74	1.48	0	2.19	1.69	2.9	2.24
	Gold	-2.34	-0.28	0.17	1.13	-0.24	-2.19	0	-0.51	1.65	0.38
	Silver	-1.7	0.17	0.88	1.43	0.14	-1.69	0.51	0	2.04	0.57
	Palladium	-2.7	-1.43	-1.02	-0.15	-1.68	-2.9	-1.65	-2.04	0	-1.29
	Platinum	-1.92	-0.59	-0.11	0.89	-1.39	-2.24	-0.38	-0.57	1.29	0
Net	-17.8	-0.2	3.1	13.3	-2.4	-15.9	2.2	-2.3	14.8	5	
Conclusion	Net-recipient	Neutral	Net-conductor	Net-conductor	Net-recipient	Net-recipient	Net-conductor	Net-recipient	Net-conductor	Net-conductor	

It is worth noting that Tables 4.3 and 4.4 do not reveal time-varying directional asymmetry patterns; the full dynamics are illustrated in Figure 4.4. Net bad-volatility spillovers dominate the good-volatility spillovers: negative shocks were driving volatility spillovers in 2016. Brexit and the US election were the most potent contributors of negative spillovers. On the other hand, in 2017, net good-volatility spillovers dominated bad-volatility spillovers, chiefly due to global economic growth.

Figure 4.5 displays the dynamic structure of net asymmetric directional spillover in semi-variances for five assets. Following Baruník et al. (2017), the net directional asymmetry spillover is defined as the difference in the response to bad- and good-volatility shocks from one market to all other markets. BTC heavily transmits net positive spillovers to other assets. In other words, net positive spillovers exhibit a greater impact. The bad volatility of palladium affects the volatility of other assets more than its good volatility, which is most likely a reflection of the deficit in the palladium market for several years. On the other hand, the extent of the net spillover of gold is time dependent. Gold heavily transmitted net negative spillovers to other assets in 2016. The pattern is related to the Brexit vote and the US election. Conversely, the second and last quarters of 2017 witnessed positive spillovers, which coincided with the strengthening of the gold price and certainly heightened with the decline in the US dollar.

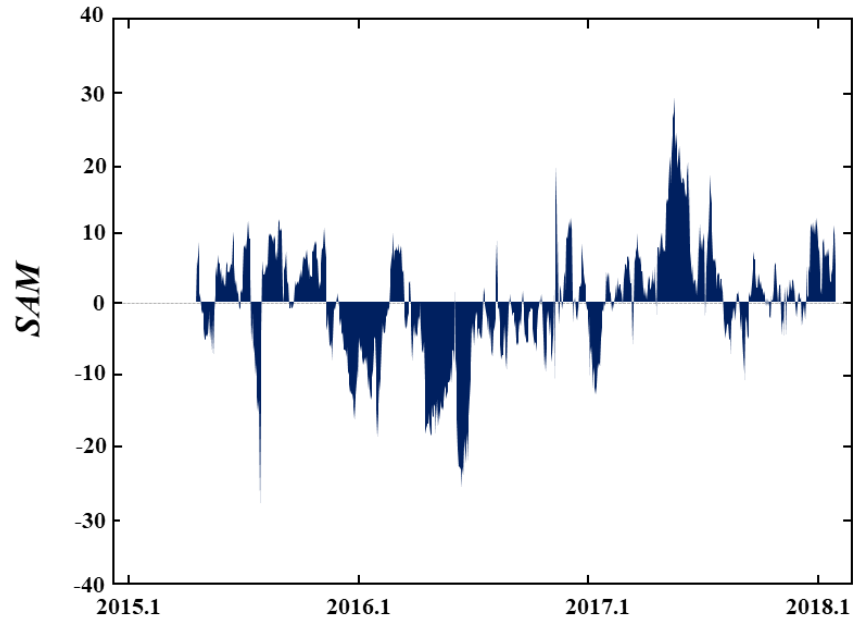
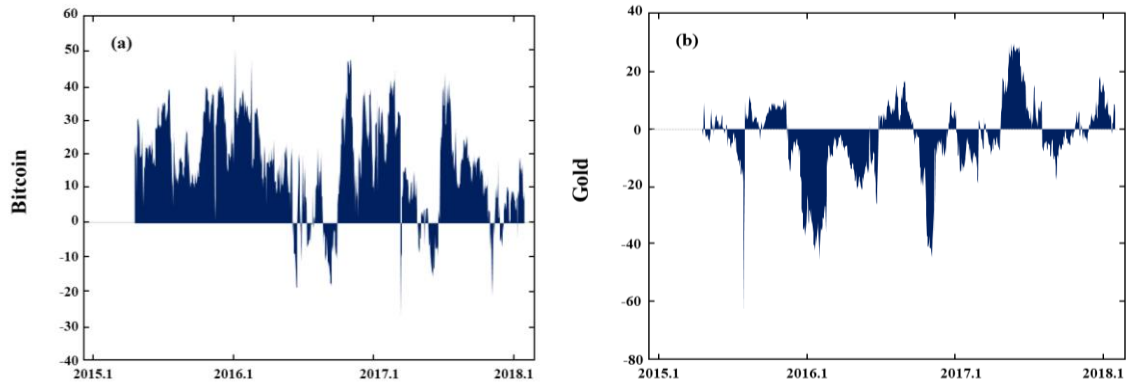


Figure 4.4: Spillover asymmetry measure: SAM

Note: This figure shows the magnitude of spillover asymmetry using the rolling-sample approach across five assets. Positive (negative) values indicate that spillovers coming from RS^+ are larger (smaller) than those from RS^- .



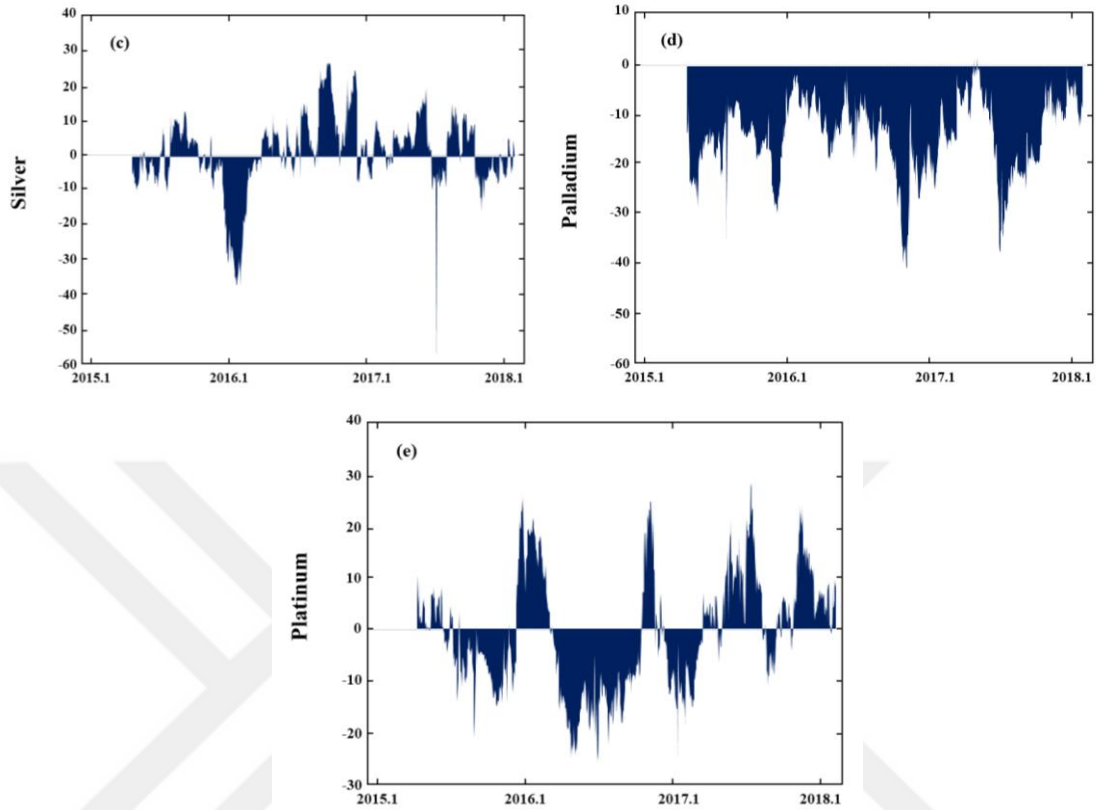


Figure 4.5: Net asymmetric directional spillover in semi-variances

Note: This figure compares the measure of net asymmetric volatility obtained for the five assets. Positive (negative) values indicate that spillovers coming from RS^+ are larger (smaller) than those from RS^- .

4.5.4. Connectedness Network

Lastly, we develop the network topology of all market connectedness—following Diebold and Yilmaz (2014, 2016)—and obtain Figures. 4.6 and 4.7, which show pairwise directional networks in semi-variances RS^+ and RS^- and net-pairwise directional networks in semi-variances RS^+ and RS^- , respectively. Figure 4.6 plots the risk spillover network diagram. All nodes show the same size and color, which do not indicate any directional power. Only edge color and thickness indicate the strength of the spillover direction. Figure 4.6 shows a clear clustering of the precious metals markets, but BTC is quite far away. Moreover, the graphical evidence shows a bi-directional pairwise connectedness across positive and negative semi-variances of precious metals, but the

connectedness between positive and negative semi-variances of precious metals and BTC is weak. More interestingly, we observe strong bi-directional connectedness between N_BTC and P_BTC. The weak connectedness between the precious metals and BTC markets validates the role of BTC and precious metals as refuge assets against portfolio risk, implying that they can provide diversification benefits and downside risk reductions.

Figure 4.7 shows the direction of the net-pairwise spillover, with different node sizes and colors representing the strength of the spillover. This figure simulates the main results for our dynamic analysis of the net-pairwise directional connectedness and provides a visualization of the complex innovation network among the five markets. We show that P_Palladium, N_Palladium, P_Silver, N_Gold, and N_Platinum (red-colored nodes) are net transmitters of volatility spillovers, while N_BTC, P_BTC, P_Platinum, N_Silver (green-colored nodes), and P_Gold (yellow-colored nodes) are net receivers of, or are neutral to, volatility spillovers from other markets. In particular, both P_Palladium and N_Palladium are the largest transmitters, indicating the dominance of palladium over other precious metals for both good and bad news. Interestingly, due to the thick red arrow from palladium to BTC, N_BTC, and P_BTC import volatility from P_Palladium and N_Palladium, suggesting that palladium is the most influential variable on the good and bad volatility of BTC. Palladium and platinum play an important role in many industries, particularly in the motor industry. Since both white metals can be used for the same function in industrial applications, palladium has been slowly substituted for platinum due to its lower cost compared to platinum. However, these two industrial commodities are scarce—even more so than gold. Despite its rarity, coupled with its growing use in everything from the automotive to the jewelry industry, palladium is cheaper than gold or silver, implying that it is currently undervalued. Our findings emphasize the importance of palladium within portfolios and provide significant policy implications for investors. Because of its limited supply and low liquidity, the palladium market sees more fluctuations than the silver and gold markets. Therefore, although palladium may be less appealing to a casual investor, it provides ample opportunity for investors seeking speculative profit.

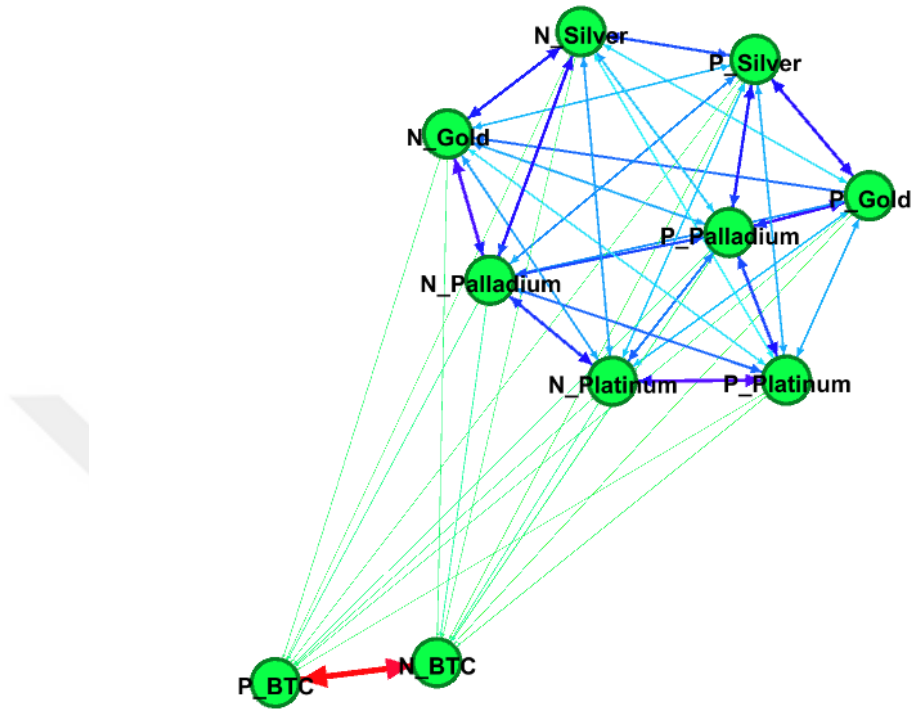


Figure 4.6: Pairwise directional network in semi-variances RS^+ and RS^-

Notes: This figure shows the pairwise directional connectedness within semi-variances RS^+ and RS^- in Table 2. The edge colors rank the strength of the pairwise directional connectedness, from red (strongest) through blue and light blue to green (weakest). The thickness of the edge arrow indicates the strength of the pairwise directional connectedness. Positive semi-variances are indicated by P_BTC (BTC), P_Gold, P_Silver, P_Palladium, and P_Platinum, whereas negative semi-variances are indicated by N_BTC (BTC), N_Gold, N_Silver, N_Palladium, and N_Platinum.

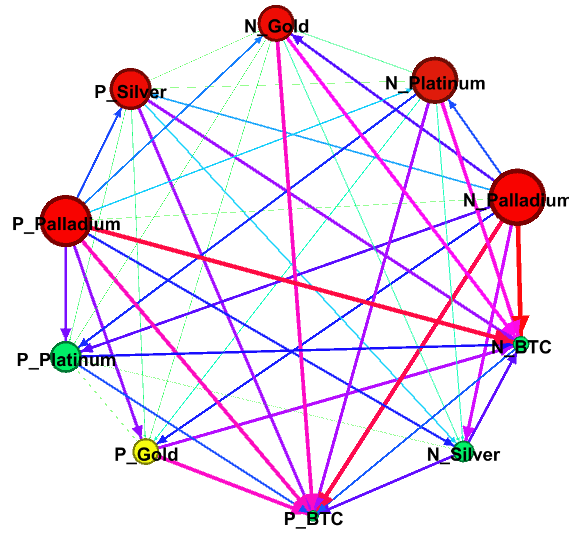


Figure 4.7: Net-pairwise directional network in semi-variances RS^+ and RS^-

Notes: This figure shows the net-pairwise directional connectedness within semi-variances RS^+ and RS^- in Table 4.3. The size of the node shows the magnitude of the net-pairwise directional connectedness, and the colors of the nodes range from red (transmitter) to yellow and green (receiver). The edge colors rank the strength of the net-pairwise directional connectedness, from red (strongest) through magenta and blue to light blue (weakest). See the notes for Figure 4.6.

4.6. Conclusions

Globalization and financial liberalization have increased the integration between financial markets and decreased opportunities for diversification. This paper examines the relationships between the intraday data of the BTC and precious metals (gold, palladium, platinum, and silver) markets. In our analysis, we use the generalized spillover index and directional spillover measure of Diebold and Yilmaz (2012), Barunik et al.'s (2017) methodology for measuring directional spillover asymmetry, and Diebold and Yilmaz's (2014, 2016) methodology on the network topology of all market connectedness.

The results show evidence of volatility spillover effects among precious metals and BTC. Moreover, the spillover trend is intensified during slowdowns in global economic activity as well as the Brexit vote and the US presidential election, evidencing financial

contagion. Palladium is the largest net contributor of spillovers followed by gold, while BTC is a net recipient of spillovers. On the other hand, we support the evidence of asymmetry in semi-volatility transmission showing that BTC heavily transmits net positive spillovers to other precious metal assets. The bad volatility of palladium influences the volatility of other assets more than its good volatility. The magnitude of the net spillover of gold is time-varying and depends on economic events. Finally, we find the network of connectedness and posit that the good and bad volatilities of palladium have the greatest impact on the good and bad volatilities of BTC.

These findings have important implications for investors and portfolio managers in terms of diversification benefits among the aforementioned five markets. BTC provides greater diversification benefits than precious metals since BTC has a much lower impact on volatility forecast error variance than precious metals. This information can help market participants diversify their risk through optimal portfolio selection. Furthermore, traders of precious metals and BTC may benefit by considering the identified asymmetries in volatility spillovers. However, Bitcoin still evolves and matures and, hence, requires time to be perceived by investors/traders/practitioners/portfolio managers as an alternative investment to gold and other precious metals.

Moreover, our findings also have implications for policy makers and regulators concerned about price stability and financial stability. Higher spillover transmissions during periods of slowdown in global economic activity or the Brexit and US election periods have led policy makers to re-formulate their economic policies and revive financial reforms and macroeconomic fundamentals in order to stabilize the financial system. Financial authorities should be able to decide on macro-prudential policies in a timely manner by drawing lessons from such periods and identifying potential sources of contagion and spillover risks that may jeopardize financial stability.

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