UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL SCIENCES

SOUTHAMPTON BUSINESS SCHOOL

Price Deviation in the Stablecoin Market and Lead-Lag Relationships in the Traditional Cryptocurrency Market

by

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Abstract

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This thesis offers new insights on the exogenous and endogenous drivers of volatility and price deviation of fiat-collateralized stablecoins across centralized exchanges. It further investigate the high-frequency lead-lag effects across centralized exchanges and non-stable cryptocurrencies. Different empirical strategies are employed to explore and understand the complex mechanism regarding stablecoin volatility and mispricings, and the information transmission reflected in the high-frequency lead–lag relationships among cryptocurrencies.

Chapter 2 identifies external drivers of stablecoin volatility, and characterizes the volatility spillover effects from external markets to stablecoins. Using a popular volatility spillover measure combined with a Time-Varying Parameter Vector Auto-Regression (TVP-VAR) model, we estimate directional spillover effects from traditional cryptocurrencies market (i.e., Bitcoin and Ethereum), traditional currency market (i.e. the USD index), and mainstream equity market (S&P 500) to four leading stablecoin markets. Our results indicate that the volatility spillovers from these markets to stablecoins are significant, and largely depend on market conditions. These significant volatility spillovers challenge the previous view of stablecoins as safe haven against non-stable cryptocurrencies and traditional assets. Robustness exercise

using an alternative model generally supports our claim. Our findings provide insightful implications for maintaining stablecoin price stability during periods of high uncertainty and trading strategies relying on the stability of stablecoins.

Chapter 3 examines the cross-exchange mispricing of stablecoins that creates arbitrage opportunities. Drawing on snapshots of limit order-book and trade data for USDT and USDC from three leading centralized exchanges, we demonstrate that such mispricing is both prevalent and persistent. Its persistence and profitability suggest that it remains exploitable across exchanges. Further analysis using market characteristics and impulse-response functions (IRFs) indicates that microstructure factors – such as order imbalance, bid–ask spreads, and market depth – together with asynchronous price across exchanges, may drive these deviations. This chapter presents the first empirical study of cross-exchanges mispricings and arbitrage in stablecoins, offering novel insights into market microstructure and highlighting a potential arbitrage pathway for market participants, with implications for reducing price deviations and enhancing market efficiency.

Chapter 4 investigates high-frequency lead-lag relationships across trading venues and assets in the cryptocurrency market. Using tick-by-tick limit order-book data, we confirm the presence of rapid lead–lag dynamics both between cryptocurrencies within the same exchange and across exchanges for the same cryptocurrency. Notably, in contrast to existing literature with lower-frequency data, our results reveal that Bitcoin often assumes a lagging position in high-frequency relationships. Further analysis of order-book behaviour suggests this lag may be linked to Bitcoin's relatively high resilience of limit order-book. An intraday examination uncovers strong seasonal patterns, showing that lead–lag effects weaken during the opening hours of the US stock market. This implies that disequilibrium in information transmission between cryptocurrency exchanges decreases when investor activity – particularly in the US – intensifies.

Collectively, the findings from this thesis deepen our understanding of market dynamics and microstructure inefficiencies surrounding stablecoins and the broader cryptocurrency ecosystem. They offer important implications for the design of stablecoins, the formulation of trading strategies, and the development of policy frameworks aimed at ensuring stability and efficiency in digital-asset markets.

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Research Thesis: Declaration of Authorship

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Title of thesis: Price Deviation in Stablecoin Market and Lead-lag Relationships in Traditional Cryptocurrency Market

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

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Chapter 1

Introduction

1.1. Research context

Over the past few decades, financial research has primarily focused on traditional assets such as stocks, bonds, and commodities. These assets have long been studied in academia, with researchers analyzing their pricing, volatility, risk management, and correlation with macroeconomic factors (Black, 1972). The Efficient Market Hypothesis (EMH), which proposes that asset prices reflect all available information, dominated much of the early literature and informed theories of market behavior and investment strategies (Fama, 1970). However, the EMH was challenged when Grossman and Stiglitz (1980) demonstrated that markets cannot be fully efficient. They argued that acquiring information is costly and time-consuming, and if prices fully incorporated all information, traders would have no incentive to gather it. The adaptive market hypothesis (AMH) built on this critique by considering the role of market participants, emphasising that efficiency is an evolving and dynamic process shaped by conditions over time (Lo, 2004). Since then, numerous studies have provided strong empirical evidence in support of the AMH (Kim et al., 2011; Hull and McGroarty., 2014, Urquhart and Hudson, 2013, Urquhart and McGroarty, 2014; Urquhart and McGroarty, 2016).

However, the rise of cryptocurrencies in the late 2000s, initiated by Bitcoin's launch in 2009 (Nakamoto, 2008), marked a major shift in financial research, and attracted significant attention from researchers. The distinctive features of cryptocurrencies – decentralized governance and blockchain technology – have prompted researchers to reassess many foundational assumptions, as traditional asset-pricing models based on discounted cash flows are ill-suited to this new asset class.

Although the idea of virtual currencies dates back to the 1980s (Bordo et al., 1989), it was the introduction of Bitcoin in 2008 that catalysed the modern cryptocurrency movement (Nakamoto, 2008). Nakamoto introduced a decentralised digital currency intended to overcome key limitations of fiat money, including dependence on central intermediaries and inflationary risks. Bitcoin sought to facilitate global capital transfers at low cost within a secure, decentralised system (Grinberg, 2012). Since then, the cryptocurrency market has expanded dramatically, with Bitcoin gaining prominence through substantial growth in transaction volume and market capitalization. Yet its high price volatility undermines its use as a stable medium of exchange or store of value, restricting its practicality for everyday transactions (Yermack, 2015). Consequently, cryptocurrencies are generally viewed as speculative assets rather than viable payment instruments, and thus Bitcoin and other volatile cryptocurrencies have not fulfilled their original promise as decentralised currencies (Selgin, 2015).

This limitation led to the development of stablecoins, designed specifically to reduce excessive volatility. By maintaining a collateralised peg, stablecoins exhibit far lower price fluctuations and are widely adopted as both a store of value and a medium of exchange in the digital-asset economy (Baur and Dimpfl, 2021).

Stablecoins are digital currencies pegged to stable assets such as gold or major fiat currencies – most commonly the US dollar, but also the euro or pound (Mita et al., 2019). They are broadly divided into collateralized and non-collateralized forms, depending on the mechanism underpinning their stability. Collateralized stablecoins are further categorized as fiat-collateralized, commodity-collateralized, or crypto-collateralized (Mita et al., 2019; Moin et al., 2020).

Fiat-collateralized stablecoin uses fiat money (e.g. the US dollar) as collateral. The issuers commit to issuing or redeeming tokens at a fixed rate at any time, such that one unit of stablecoin equals one unit of fiat currency. For example, USDT, the most widely used stablecoin, is pegged to US dollar[1]. The issuer, Tether, promises a one-to-one exchange with the US dollar when issuing and redeeming USDT, which means one can buy or sell USDT with Tether at 1 USD price.

Commodity-collateralized stablecoins use commodities, such as gold and oil, as collateral. Despite using different types of collateral, these stablecoins operate similarly to fiat-

[1] https://tether.to/en/

collateralized stablecoins by holding reserves that back their tokens. A representative example is Tether Gold (XAUT), a stablecoin pegged 1:1 to one fine troy ounce of gold. It provides a digital token representing ownership of physical gold securely stored in designated vaults[2].

The last type of collateralized stablecoin is crypto-collateralized stablecoin. This type of stablecoins use other, typically volatile, cryptocurrencies as collateral. The mechanism of crypto-collateralized stablecoins works as follows: to issue crypto-collateralized stablecoins, a specified amount of cryptocurrency is locked in a smart contract, which then generates the requested stablecoins in return (Roberts, 2022). To mitigate declines in collateral value, they are usually over-collateralized (often by around 150%). DAI, the most prominent example, is collateralized by a mix of cryptocurrencies through MakerDAO. For instance, depositing 1 ETH valued at USD 1,500 allows a maximum draw of USD 1,000 in DAI; if ETH falls in value, additional collateral is required.

Non-collateralized (algorithmic) stablecoins are not backed by assets. Instead, their stability is maintained through algorithms and smart contracts that adjust supply. Simply put, if the price of the stablecoin falls below the target, then tokens are burned to reduce supply; if the price exceeds the target, then new tokens are issued. However, due to the lack of collateral, this type of stablecoin are highly vulnerable during severe market stress, as seen with the collapse of Terra (Lyons and Viswanath-Natraj, 2023).

Due to the design mechanism and stability of price, stablecoins have thus become widely used as a medium of exchange and store of value within cryptocurrency markets (Koutsoupakis, 2020; Griffin and Shams, 2020). They are also regarded as safe-haven assets or portfolio diversifiers against volatility in traditional cryptocurrencies (Baur and Hoang, 2021; Wang et al., 2020; Xie et al., 2021). More recently, however, attention has shifted towards their excess volatility. Despite their collateral mechanisms, stablecoins have been found to be less stable than fiat currencies, raising questions about their effectiveness

[2] https://coinmarketcap.com/currencies/tether-gold/#About

(Hoang and Baur, 2021). Studies attribute this instability to correlations with volatile cryptocurrencies (Jarno and Kołodziejczyk, 2021; Grobys et al., 2021, Kristoufek, 2021).

However, despite the prominence stablecoins gained in existing research,the mechanisms through which volatility is transmitted from both cryptocurrencies and traditional financial markets to stablecoins remain underexplored. Prior research often overlooks the role of volatility spillovers, even though these may pose risks to trading strategies that treat stablecoins as safe havens or diversifiers. Understanding this is important as significant spillover effects may bring potential risks to trading strategies relying on their stability. Chapter 2 addresses this gap by investigating volatility spillovers from related markets to fiat-collateralised stablecoins. We further suggest that the results for fiat-collateralised stablecoins may extend to other categories, since external shocks that affect fully backed stablecoins are also likely to influence those backed by alternative mechanisms (Jarno and Kołodziejczyk, 2021; Lyons and Viswanath-Natraj, 2023).

Moreover, besides correlation with volatile assets, the excess volatility of stablecoins also faced criticism due to their design mechanism. Prior research generally argues that fully collateralised stablecoins are more stable than algorithmic ones due to more arbitrage activities (Jarno and Kołodziejczyk, 2021; Kozhan and Viswanath-Natraj, 2021; d'Avernas et al. 2022; Gadzinski et al., 2023). Specifically, algorithmic stablecoins, such as TerraUSD, are particularly prone to devaluation when under-collateralised as the absence of clear arbitrage pathways undermines confidence in governance tokens (Lyons and Viswanath-Natraj, 2023). Arbitrage therefore plays a critical role in maintaining stablecoin stability, especially for fully backed stablecoins (Pernice, 2021; Lyons and Viswanath-Natraj, 2023).

Arbitrage is essential because, regardless of type, stablecoins ultimately depend on market-based arbitrage to correct price deviations between primary and secondary markets. Prior literature highlights this role: Pernice (2021) shows that arbitrage enhances the stability of theoretical stablecoin models, while Lyons and Viswanath-Natraj (2023) demonstrate that arbitrage reduces deviations from pegs in practice.

However, these research are limited to the arbitrage activities between primary and secondary market, overlooking the potential arbitrage opportunities within secondary markets. The primary market is where tokens are issued or redeemed directly with the issuer at the target peg (e.g. Tether). The secondary market involves transactions between users on exchanges at market prices. Arbitrage in secondary markets is particularly important because it typically requires lower capital and incurs lower transaction costs, making it more accessible and effective for correcting subtle de-pegging. As stablecoins often serve as the entry point for investors, maintaining price stability in these markets is crucial for managing transaction costs (Mita et al., 2019; Moin et al., 2020).

Accordingly, Chapter 3 investigates mispricing and arbitrage opportunities across centralized exchanges, examining both their persistence and potential profitability. We show that stablecoin mispricing largely occurs in secondary markets, driven by market microstructure factors and differences in price efficiency across exchanges.

Finally, we turn to price discovery and information diffusion in cryptocurrency markets. Unlike traditional assets, cryptocurrencies are traded across multiple centralized exchanges, creating fragmentation. This fragmentation hinders the uniform transmission of information, potentially leading to delays in price discovery and the emergence of lead–lag effects.

Research on price discovery in cryptocurrency market is still at an early stage. Existing studies generally find that Bitcoin and Ethereum broadly lead other cryptocurrencies. For instance, Yarovaya and Zieba (2022) analyze the lead–lag relationships among the top 30 cryptocurrencies and confirm Bitcoin's leading role, while Sifat et al. (2019) document a bidirectional relationship between Bitcoin and Ethereum. These studies, however, use equally spaced daily or hourly data. We argue that these lead-lag relationship with low frequency dataset filters much useful short-term information to practical tradings, as the lag length in high frequency trading period are usually seconds or even sub-seconds (O'Hara, 2015; Alsayed and McGroarty, 2014). For this reason, chapter 4 focus on the high-frequency lead-lag relationships in cryptocurrency market. We focus on the fast lead-lag relationships between cryptocurrencies in same exchanges, and the fast lead-lag relationships of same cryptocurrencies in different exchanges. Understanding fast lead-lag relationships is important as these fast relationships might provide useful extra information to practical trading.

Overall, this thesis covers different types of cryptocurrencies, including stablecoins and traditional volatile cryptocurrencies. It addresses highly debated issues such as stablecoin volatility and mispricing, as well as lead–lag relationships among major cryptocurrencies. In Chapter 2, we focus on the mechanism of volatility transmission from related markets to stablecoin markets, investigating the volatility spillover effects from these markets to stablecoins. Chapter 2 also identifies potential risks in previous trading strategies that treat stablecoins as safe havens or diversifiers. In Chapter 3, we examine the mispricing and arbitrage opportunities of stablecoins across exchanges. Chapter 3 sheds new light on arbitrage strategies for stablecoins, identifying factors that contribute to the emergence of mispricing. In Chapter 4, we analyse high-frequency lead–lag relationships across exchanges and leading volatile cryptocurrencies, providing evidence of the lagging position of Bitcoin and Ethereum, and offering new insights into the factors that shape these lead–lag dynamics.

1. 2. Theoretical background and methodology

This thesis is based on several key theories that underpin financial economics, including spillover theory, market integration theory, arbitrage theory, the EMH, the AMH, and theoretical work on price discovery. In this section, we introduce how these theories are related to this study, and outline the methodologies applied to examine them.

1. 2. 1. Theory of spillover and market integration

Ito & Roley (1987) was the first attempt to explore the idea of volatility spillover effect across financial markets, they found a significant linkage between the fluctuations of the Japanese and U.S. exchange markets. Engle et al. (1988) proposed "Meteor Showers" hypothesis, highlighting the impact from related markets. The Meteor Showers hypothesis suggests if a shock increases the volatility of one market, the same shock might also intensify the volatility of related markets.

Ito and Roley (1987) first attempted to explore volatility spillover effects across financial markets, finding a significant linkage between fluctuations in the Japanese and US exchange markets. Engle et al. (1988) later proposed the 'meteor showers’ hypothesis, which highlights the impact of related markets. The hypothesis suggests that if a shock increases the volatility of one market, then the same shock may also intensify volatility in related markets.

Before the concept of spillovers, the term ‘financial contagion’ firstly appeared in the literature, borrowed from medicine to describe the spread of diseases. Following the Thai currency crisis in 1997, which spread rapidly across global markets, the term was also used to capture the transmission of financial distress (Liu and Pan, 1997; Bekaert and Harvey, 2003). Building on these concepts, subsequent studies (Diebold and Yilmaz, 2009, 2012, 2015; Forbes, 2012) define spillover effects as the impact of shocks generated in one financial market on other markets, fully accounting for linkages between financial assets and markets across the system. In other words, spillovers describe the transmission of shocks from one market to another.

The volatility spillover theory emphasises how market shocks can spread across assets and markets. According to prior literature, two main factors affect spillovers: market integration and financial contagion (Jiang et al., 2012; Bekaert and Harvey, 2003; Adams et al., 2014; Jalal et al., 2020). During normal periods, spillovers largely depend on market integration, meaning the degree to which financial markets are connected (Liu and Pan, 1997; Bekaert and Harvey, 2003). During crises, however, spillovers are mostly driven by financial contagion, which refers to the propagation of shocks from one market to others, often leading to temporary and sharp increases in spillover effects (Bekaert and Harvey, 2003). Together, these factors imply that volatility spillovers intensify during crises or periods of extreme volatility(Forbes and Rigobon, 2002). Consequently, spillovers during such periods tend to be asymmetric, as large negative returns are more strongly associated with intensified spillover effects than large positive returns, given that crises and crashes are typically linked to downturns.

1. 2. 2. Methodology of spillover effects

To quantify and measure volatility spillovers, GARCH model and VAR model are the most commonly used methodologies in previous empirical analysis (Soriano and Climent, 2005). The GARCH model is derived from the Autoregressive Conditional Heteroskedasticity (ARCH) model (Engle, 1982), which provides a useful tool in forecasting financial time series. GARCH has been largely used to measure the volatility transmission across financial markets, including cryptocurrency market (Inagaki, 2007; Bouri et al., 2021; Zhang et al., 2022). And different extensions (i.e. T-GARCH, E-GARCH and GJR- GARCH) are aiming to address different issues of financial datasets. However, employing all extensions to address all problems simultaneously is complex. Also, using GARCH requires a certain level of correlation among financial variables, otherwise the results might be invalid (Maaitah, 2020).

Another widely used method for measuring spillover effects is the VAR model, proposed by Sims (1980) to capture correlations and interdependencies among variables within a system. The most influential extensions were introduced by Diebold and Yilmaz (2009, 2012, 2015), who combined the VAR framework with variance decomposition and impulse response functions to examine volatility spillovers across markets. Their approach improves robustness by mitigating ordering problems. Furthermore, Antonakakis and Gabauer (2017) extended the Diebold–Yilmaz (DY) methodology by incorporating the TVP–VAR model, which avoids arbitrary window-size selection and is more resilient to outlier observations. In this thesis, we apply the DY method combined with the TVP–VAR model to investigate volatility spillover effects from related markets to stablecoin markets.

1. 2. 3. Theory of arbitrage

Arbitrage is defined as the trading activity of exploiting of price differences between markets or instruments to generate a risk-free profit. The concept of arbitrage is much shaped by the Law of One Price (LOOP) and Efficient Market Hypothesis (EMH), which hold that identical assets should not trade at different prices in efficient markets. Fama (1970) incorporates the concept of arbitrage into the Efficient Market Hypothesis (EMH), highlighting the role of arbitrageurs in eliminating inefficiencies in markets, ensuring that prices reflect all available information. Later, Lo (2004) introduced the AMH, suggesting that arbitrage is not a guaranteed risk-free activity in practice. Instead, it should be viewed as a dynamic process shaped by the adaptive behaviour of market participants and evolving market conditions.

The limits and risks of arbitrage have been widely discussed in prior literature (Shleifer and Vishny, 1997; Mitchell et al., 2002). Two major risks are particularly important: fundamental risk and inventory risk. Fundamental risk refers to the possibility that mispricings may persist for some time, exposing the arbitrageur to the chance that prices move further away from their fundamental values before correcting. Such risks may arise due to irrational noise traders or imperfect information (De Long et al., 1990; Mitchell et al., 2002). Inventory risk refers to the potential loss when arbitrageurs must hold positions in mispriced assets while awaiting convergence, during which time prices may move unfavourably.

Shleifer and Vishny (1997) highlighted that both fundamental and inventory risks can force arbitrageurs into liquidation if prices diverge further, particularly under margin calls. Inventory risk often accompanies fundamental risk, as arbitrageurs may face high capital costs if they rely on borrowed funds. Consequently, even when mispricings eventually converge, arbitrageurs may be unable to sustain positions long enough to realise gains.

Beyond these risks, arbitrageurs also face practical costs and constraints when executing trades. These include short-selling costs, leverage and margin restrictions, and limits on equity capital (Gromb and Vayanos; 2010). Information acquisition is another key constraint, as it can be costly (Grossman and Stiglitz, 1976, 1980), and in high-frequency trading environments valuable information may expire within seconds (Alsayed and McGroarty, 2014; Marshall et al., 2013). Arbitrageurs therefore target only those opportunities that can cover the high cost of rapid information acquisition (Marshall et al., 2013). In cryptocurrency markets, additional limits such as trading speed, short-selling constraints, technical infrastructure, and capital controls have also been documented (Fischer et al., 2019; Makarov and Schoar, 2020).

1. 2. 4. Methodology of detecting arbitrage opportunities

In Chapter 3, we investigate the mispricing of stablecoins that enables arbitrage across exchanges. We collect historical limit order book data for stablecoins from several exchanges to examine whether arbitrage opportunities exist. The arbitrage strategy is straightforward: we track identical stablecoins across exchanges, and if the bid price on one exchange is higher than the ask price on another – and the difference exceeds trading costs – then an arbitrage opportunity exists. In such cases, investors can buy at the lower ask price and sell at the higher bid price. In addition, given the importance of time duration, we only consider arbitrage opportunities that last longer than one second. We regard this as sufficient for arbitrageurs to identify and exploit, as trading in cryptocurrency markets is extremely fast (Aleti & Mizrach, 2021).

We also analyse the determinants of arbitrage occurrence and profitability using both daily and intraday market characteristics. At the daily level, we apply linear regression to test how bid–ask spreads, order imbalance, and trading volume affect the frequency and profitability of mispricing. At the intraday level, we examine changes in market microstructure factors in the minutes before, during, and after each arbitrage opportunity arises, to assess their contribution to mispricing. Finally, following Chordia et al. (2005), we employ impulse response function tests to investigate whether differences in price discovery speed across exchanges contribute to the arbitrage opportunities we observe.

1. 2. 5. Theory of lead-lag effect

The essence of the lead–lag effect lies in the fact that market participants react to the arrival of new information at different speeds. In finance, the lead–lag effect refers to the phenomenon where the price movements of one financial asset precede and potentially influence the price movements of another. If one market reacts more quickly to new information while another responds more slowly, a lead–lag relationship emerges (Chan, 1992).

The theoretical foundation of the lead–lag effect is largely based on the EMH (Fama, 1970), the AMH (Lo, 2004), information diffusion theory, and theoretical work on price discovery. The EMH suggests that prices should fully reflect all available information in efficient markets. This implication relies on the assumption that new information is transmitted instantaneously and simultaneously across the market. In practice, however, information is neither distributed nor processed uniformly, which leads to the presence of lead–lag effects.

Within the AMH, traditional theories of market efficiency are reinterpreted within an evolutionary framework, including implications for information and price discovery. According to the AMH, lead–lag effects can arise as market participants adjust to changing conditions at different speeds, owing to limits on attention or unequal access to information (Hong & Stein, 1999). These frictions may generate temporary disequilibria, where leading markets incorporate and react to new information faster than lagging markets (Grossman & Stiglitz, 1980).

The theory of the lead–lag effect is also closely linked to market microstructure, as both concern the mechanisms of market characteristics, information dissemination, and price formation. Liquidity and trading volume often play central roles in price discovery, since information is transmitted primarily through trading activity (Hasbrouck, 1995; Chordia & Swaminathan, 2000). Ultimately, lead–lag effects are strongly correlated with information transmission in markets, and any factors that influence this transmission – such as information asymmetry or market segmentation – will also affect lead–lag relationships and price discovery (Easley and O'hara,1992; Eun and Shim, 1989).

1. 2. 6. Methodology of lead-lag effect

In Chapter 4, we analyse high-frequency lead–lag relationships both between the same cryptocurrencies traded on different exchanges and between different cryptocurrencies traded on the same exchange, using snapshots of limit order book data. To address the challenges of irregular and asynchronous tick data, we apply the Hayashi–Yoshida (HY) method proposed by Hayashi and Yoshida (2005). This method overcomes the substantial data loss problem, a major disadvantage of sparse sampling approaches. It enables the analysis of two irregularly spaced time series of different lengths and allows examination of high-frequency lead–lag relationships. By calculating the contemporaneous and non-contemporaneous correlations between two irregular tick datasets with misaligned lag lengths, we are able to identify the optimal lag length corresponding to the highest correlation.

1. 3. Research gaps, objectives and contributions

The research gaps, objectives, and contributions of each chapter are presented next.

The research gaps and objectives in Chapter 2 are as follows:

As Bitcoin and other volatile cryptocurrencies fail to serve as a medium of exchange due to high fluctuations (Baur and Dimpfl, 2021), stablecoins were created to fulfil cryptocurrency's original promise of functioning as a medium of exchange with much lower volatility (Yermack, 2015). Owing to their pegging mechanism and relative stability, stablecoins are not only used to trade volatile cryptocurrencies (Kristoufek, 2021) but also play important roles as potential safe havens and effective diversifiers in portfolios against non-stable cryptocurrencies and stock markets (Baur and Hoang, 2021; Wang et al., 2020; Xie et al., 2021). More recently, however, growing empirical evidence suggests that stablecoins are not absolutely stable, exhibiting higher volatility than fiat currencies (Duan and Urquhart, 2023; Hoang and Baur, 2021). This excess volatility is attributed both to design mechanisms (Gadzinski et al., 2023; Jarno and Kołodziejczyk, 2021) and to their correlation with volatile cryptocurrencies (Hoang and Baur, 2021; Groby et al., 2021; Griffin and Shams, 2020).

Overall, prior literature has evolved from viewing stablecoins as potential safe haven assets to increasingly questioning their stability. However, little is known is the volatility transmission from external related markets to stablecoins markets. We identify a research gap in that few studies systematically examine volatility spillovers from traditional assets and non-stable cryptocurrencies into stablecoin markets when considering them as safe havens or diversifiers. Understanding this is important, as significant spillover effects may create risks for trading strategies relying on the stability of stablecoins.

Therefore, in chapter 2, we aim to fill this research gap by addressing two research questions: (i) what drives the stablecoins volatility? (ii) How does the impact of these drivers on stablecoins volatility evolve over time? To address these two research questions, we investigate spillover effects between stablecoins and related markets, including Bitcoin, Ethereum, the S&P 500, US Dollar Index (DXY) and gas price of Ethereum blockchain.

Consequently, Chapter 2 contributes to the literature in the following way.

- To the best of our knowledge, this is the first empirical study to analyse risk transmission and volatility spillovers from external markets, particularly non-crypto assets, to stablecoins. Chapter 2 highlights the external drivers of stablecoin volatility. Our findings undermine trading strategies that treat stablecoins as safe havens or diversifiers against cryptocurrencies and traditional assets (Baur and Hoang, 2021; Xie et al., 2021; Feng et al., 2024). This study highlights the importance of accounting for spillover effects when developing trading strategies

The research gaps and objectives in Chapter Three are:

The introduction of stablecoins aims to solve the problem of the high volatility of traditional cryptocurrencies. By maintaining collateralised pegs, stablecoins are able to sustain much lower volatility than traditional cryptocurrencies, and they thus play a key role as a store of value and medium of exchange in the crypto economy (Yermack, 2015; Kristoufek, 2021). For fiat-collateralised stablecoins, issuers commit to issuing or redeeming the stablecoin for collateral at a fixed rate. However, despite the existence of this pegging mechanism, the prices of stablecoins are not as stable as fiat currencies (Hoang and Baur, 2021). Stablecoins frequently experience mispricing and price deviations from their peg in secondary markets, such as cryptocurrency exchanges (Lyons and Viswanath-Natraj, 2023).

These mispricings and price deviations attract arbitrage activities, and previous research provides evidence that arbitrage can reduce deviations and enhance the price stability of stablecoins (Kozhan and Viswanath-Natraj, 2021; Lyons and Viswanath-Natraj, 2023; Pernice, 2021). However, existing literature largely focuses on mispricings and arbitrage opportunities between primary and secondary markets, while potentially overlooking opportunities within secondary markets. Moreover, the high transaction costs and entry barriers in primary markets limit arbitrageurs' ability to exploit small price deviations.

Therefore, to fill this research gap, the main objective of chapter 3 is to answer two research questions (i) Do mispricings of stablecoins exist across cryptocurrency exchanges that enable arbitrage? (ii) What factors contribute to the occurrence and potential profitability of these arbitrage opportunities? Answering these questions is important, as identifying additional arbitrage routes could help eliminate smaller price deviations and improve the financial stability of stablecoins and the broader crypto ecosystem. To do so, we collect the tick level snapshot of limit order book data for two leading stablecoins, USDT and USDC, from three major exchanges, Kraken, Bitstamp and BinanceUS. We investigate the mispricings allowing arbitrage across exchanges.

Accordingly, Chapter 3 contributes to the literature on the mispricings and arbitrage in stablecoin markets in the following two significant ways:

- This chapter identifies a new arbitrage route in stablecoin markets by exploiting cross-exchanges mispricings, shifting attention from arbitrage between primary and secondary markets to opportunities within secondary markets. It also provides empirical evidence that such arbitrage opportunities are profitable and exploitable, which may further reduce stablecoin price deviations (Lyons and Viswanath-Natraj, 2023). The rapid correction of these mispricings aligns with the dynamic process described in the Adaptive Market Hypothesis.

- Chapter 3 also shed new lights on the drivers of mispricings in stablecoins. Through the analysis of market microstructure when mispricing-based arbitrage occurs, we find that microstructure factors, such as order imbalance, bid-ask spreads and market depth, might be one driver of mispricings. Using impulse response function (IRF) analysis, we investigate the price discovery speed of each centralized exchanges. Our results indicate that asynchronous price adjustments to information across exchanges may be another driver of stablecoin mispricings.

The research gaps and objectives in Chapter Four are:

Unlike traditional assets, cryptocurrencies such as Bitcoin and Ethereum are traded on numerous exchanges, which introduces challenges related to price discovery and gives rise to lead–lag problems. Existing literature provides empirical evidence that lead–lag effects are widespread in the crypto space, with Bitcoin and Ethereum broadly holding leading positions relative to other cryptocurrencies (Qureshi et al., 2020; Yarovaya and Zięba, 2022; Sifat et al., 2019). These studies are mostly conducted with equally spaced datasets at daily or hourly frequency (Qureshi et al., 2020; Makarov and Scholar, 2020; Yarovaya and Zięba, 2022; Sifat et al., 2019). However, research based on relatively low-frequency datasets has two major limitations. First, equally spaced datasets lead to substantial data loss. Second, low-frequency lead–lag relationships do not provide useful information for practical trading, since fast lead–lag information typically becomes outdated within seconds or even sub-seconds (O'Hara, 2015; Alsayed and McGroarty, 2014). We therefore argue that there is a research gap in that high-frequency lead–lag relationships have been largely ignored in the existing literature. Understanding these dynamics is important, as high-frequency lead–lag effects are essential to capturing rapid price movements and may provide valuable information for trading strategies.

Chapter 4 addresses this gap by answering two research questions: (i) Do high-frequency lead–lag effects exist for the same cryptocurrency across different exchanges? (ii) Do high-frequency lead–lag effects exist between cryptocurrencies on the same exchange? To answer these questions, we collect tick-level limit order book data for leading cryptocurrencies and investigate fast lead–lag relationships of mid-prices.

Consequently, Chapter 4 contributes to the literature in the following two significant ways.

- Using high-frequency data, Chapter 4 identifies sub-second lead–lag relationships both within the same exchange and across exchanges for the same cryptocurrency. We extend existing research on lead–lag effects in cryptocurrency from daily and hourly datasets to tick-level analysis. These relationships reveal the existence of potential disequilibria within and across centralized exchanges. This study also identifies the lagging position of Bitcoin at the high-frequency level, highlighting the distinct lead–lag dynamics of cryptocurrencies when examined at finer timescales.

- As a further contribution, Chapter 4 sheds light on the factors that may affect high-frequency lead–lag effects in cryptocurrency markets. The results indicate that lead–lag positions may be associated with market depth and order book resilience, while lag length appears to be correlated with periods of intensive market activity.

1. 4. Schematic representation of the thesis

Chapter 1 gives a general introduction and background on cryptocurrencies and stablecoins, followed by a brief overview of the theoretical background, methodology, and the research gaps, objectives, and contributions of each chapter. Chapter 1 systematically outlines the purpose of this thesis.

Chapter 2 examines the volatility transmission mechanism from external markets to stablecoin markets. In this chapter, spillover measures combined with a TVP–VAR model are used to analyse and identify the magnitude of volatility spillovers from external markets to stablecoin markets. A robustness check using an alternative Vector Auto-Regression model is applied to validate the results.

Chapter 3 focuses on the mispricing of stablecoins that enables arbitrage within secondary markets. This chapter introduces a new arbitrage route for stablecoins and provides empirical evidence that such opportunities are both profitable and exploitable. Analysis of market characteristics and IRFs reveals that microstructure factors and asynchronous price adjustments across exchanges may be two drivers of cross-exchange mispricing in stablecoin markets.

Chapter 4 investigates high-frequency lead–lag relationships among cryptocurrencies and across centralized exchanges. A recent advancement in the statistical measurement of lead–lag relationships is applied, allowing us to analyse non-contemporaneous correlations between different assets using tick-by-tick data. Further analysis suggests that market depth and order book resilience are associated with lead–lag positions, while intraday seasonality analysis indicates that lead–lag effects diminish during the opening hours of the US market.

Chapter 5 provides a comprehensive conclusion, summarizing the main findings and implications of each chapter in this thesis. It also discusses the limitations of the study and offers suggestions for future research.

Chapter 2

Drivers of Stablecoin Volatility: Evidence from Spillover Analysis on volatile cryptocurrencies and traditional asset

Chapter 2

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Abstract

This paper investigates potential drivers of stablecoins volatility by utilizing daily data from November 1, 2018, to December 31, 2023. We apply linear regression and a spillover effects measure based on the time-varying parameter vector autoregression (TVP–VAR) model. The analysis examines the impact of the cryptocurrency market (i.e. Bitcoin and Ethereum), the currency market (i.e. the US Dollar Index), the equity market (i.e. the S&P 500), and blockchain infrastructure factors (i.e. Ethereum gas prices) on the volatility of four leading fully collateralized USD-pegged stablecoins: USDT, USDC, TUSD, and USDP. The results reveal that non-stable cryptocurrencies and traditional assets contribute significantly to stablecoin volatility, with the strength of these effects being time-varying and largely dependent on market conditions. Moreover, the findings demonstrate asymmetric spillover effects, where external markets transmit stronger volatility to positive price deviations than to negative deviations.

Key words: Cryptocurrency, Stablecoin, Volatility, Connectedness.

2.1. Introduction

The cryptocurrency market has increasingly been recognized as a new asset class (Corbet et al., 2018) and has rapidly become an important component of the global financial system (Gajardo et al., 2018). The first stablecoin, BitUSD, was introduced in 2014 (Piech). As a new type of cryptocurrency, its introduction considerable attention from both academic researchers and industry professionals as stablecoins hold the potential to fulfill cryptocurrency's original promise of serving as a medium of exchange (Yermack, 2015). In contrast, due to its high volatility, Bitcoin struggles to function effectively as a medium of exchange and has limited utility as a risk diversifier (Baur and Dimpfl, 2021).

Stablecoins are cryptocurrencies pegged to fiat currencies or other assets. They can be mainly classified into four types[3] according to their pegged assets (Mita et al, 2019; Moin et al, 2020). Fiat-pegging is the most common, typically pegging to the US dollar or the euro. The two largest stablecoins, USDT and USDC, are both pegged to the US dollar. By maintaining a collateralised peg and full reserves, stablecoins are much less volatile than other cryptocurrencies, equities, and commodities (Hoang and Baur, 2021). Consequently, they are regarded as the primary payment method and medium of exchange in cryptocurrency markets, as well as serving as safe havens against the volatility of traditional cryptocurrencies during market turmoil (Baur and Hoang, 2021). Stablecoins are also used to support the prices of traditional cryptocurrencies during downturns (Griffin and Shams, 2020).

In recent years, stablecoin has gained rapid development. A BIS report shows that the circulation of major stablecoins reached USD 120 billion by late 2021 (Doerr et al., 2021). Mizrach (2022) reports the 24-hour exchange turnover of USDT exceeded 70 billion USD in the Q1 2022, a figure comparable to the daily trading volume of the New York Stock Exchange.

As stablecoin gain prominence, increasing attention has been paid to the question of how stable they actually are. On the one hand, it is widely acknowledged that their fiat-pegged design grants them greater price stability, making them resemble major currencies more than

[3] Fiat-collateralized, crypto-collateralized, commodity-backed, and algorithmic

speculative assets (e.g., BIS, 2019; IMF, 2019). Other research also supports the view that stablecoins exhibit stable price behaviour, highlighting their role as a potential safe haven and effective diversifier in investment portfolios. Stablecoins have been shown to help hedge against the volatility of traditional cryptocurrencies (Baur and Hoang, 2021; Wang et al., 2020; Xie et al., 2021) as well as fluctuations in global stock markets (Feng et al., 2024; Paeng et al., 2024).

However, more recent evidence suggests that stablecoins often fail to match the stability of fiat currencies and exhibit excess volatility (see Duan and Urquhart, 2023; Hoang and Baur, 2021; Grobys et al., 2021). Stablecoins are found to be linked with non-stable cryptocurrencies through trading volume (Hoang and Baur, 2021; Let et al., 2023) and price volatility (Grobys et al., 2021, Kristoufek, 2021;). Additionally, as a medium of exchange in cryptocurrency market, stablecoins are correlated with trading activity in non-stable cryptocurrencies (Kristoufek, 2021; Griffin and Shams, 2020; Wei, 2018). While most studies focus on the correlation between stablecoins and non-stable cryptocurrencies, only limited evidence examines their link with traditional assets, particularly stock markets (Feng et al., 2024; Paeng et al., 2024).

Taken together, prior literature has evolved from viewing stablecoins as potential safe haven assets to increasingly questioning their stability. More recent studies focus on their correlations with other financial markets, yet relatively little attention has been given to the transmission of volatility from external markets into stablecoins. In particular, few studies systematically examine the extent to which volatility from traditional assets and non-stable cryptocurrencies spillovers into stablecoin markets. Understanding this is important, as significant spillover effects may pose risks to trading strategies that rely on stablecoin stability. To fill this literature gap, we set out to answer two research questions in this study (i) what drives the stablecoins volatility? (ii) How does the impact of these drivers on stablecoins volatility evolve over time?

To address these research questions, we examine the spillover effects between stablecoins and related markets. Spillovers can be broadly understood as shocks or uncertainty that transmit across markets depending on their degree of interdependence and financial linkage (Liu and Pan, 1997; Bekaert and Harvey, 2003). The basic mechanism of spillover effects involves the spread of distress through capital flow or information transmission between markets (Ross, 1989; Bekaert and Harvey, 2003). Diebold and Yilmaz (2009, 2012, 2015) define spillovers as a measure of dependence between markets and propose an econometric framework to quantify them. By investigating spillovers, we are able to analyze the mechanism of transmission of volatility between stablecoin markets and related markets, thereby identifying how shocks in external markets influence stablecoin dynamics. In this study, we focus on related markets including Bitcoin, Ethereum, the S&P 500, the DXY, and Ethereum gas prices, as these factors are likely to affect stablecoin volatility for the following reasons.

As representatives of traditional cryptocurrencies, Bitcoin and Ethereum are found to be correlated with stablecoins (Griffin and Shams, 2020; Kristoufek, 2021; Łęt et al., 2023). However, few studies examine the spillover effects between the volatility of non-stable cryptocurrencies and stablecoins. Analyzing these volatility spillover effects would provide new insights to the trading strategy in prior literature which rely on stablecoin as safe haven against huge fluctuation of traditional cryptocurrencies.

The DXY represents the performance of the US dollar against six major currencies. Much prior research attempts to explain the excess volatility of stablecoins through correlations with non-stable cryptocurrencies, potentially overlooking the influence of traditional markets, especially the currency market. According to the theory of spillover effects (Bekaert and Harvey, 2003), one important feature of market linkage is unrestricted capital flow between markets. This holds for stablecoin markets and the US dollar market, as capital moves freely between the two. Consequently, traders may buy or sell USD-pegged stablecoins in response to fluctuations in the DXY. For this reason, we consider the DXY to be a potential driver of stablecoin volatility.

The S&P 500 index, as a benchmark of the mainstream equity market, plays a pivotal role in the global financial landscape, and exerts significant spillover effects on a range of markets, including equities, commodities, and the foreign exchange (Forbes and Rigobon, 2002; Mensi et al., 2013; Mishra et al., 2007). Previous research highlights risk transmission between the S&P 500 and traditional cryptocurrencies, showing strong spillover effects from equities to cryptocurrency markets (Lento and Gradojevic, 2021; Hung, 2022). However, despite stablecoins being a major form of digital currency within the cryptocurrency ecosystem, spillovers between the S&P 500 and the stablecoin market have been largely overlooked. Only limited work has considered correlations between stablecoins and global equity markets (Feng et al., 2024; Paeng et al., 2024). Investigating this relationship can therefore provide important insights into the effectiveness of trading strategies that use stablecoins as hedges or safe havens for equity assets.

Finally, Ethereum gas prices – representing blockchain transaction costs – constitute another potential driver. We focus on Ethereum because all of the sampled stablecoins are traded on this blockchain. Transaction costs and trading infrastructure factors are recognised as important drivers of price volatility in traditional markets (Wade, 1991; Jones and Seguin, 1997; Pagnotta and Philippon, 2018). Empirical studies also show correlations between transaction costs and price volatility in cryptocurrency markets (Eska et al., 2024; Svogun and Bazán-Palomino, 2022), and yet their role in explaining stablecoin volatility has been overlooked. Accordingly, we examine whether Ethereum gas prices influence stablecoin volatility.

To analyze the volatility spillovers between stablecoins and these related markets, we apply the Time-Varying Parameter Vector Auto-Regression (TVP-VAR) model combined with the dynamic connectedness framework proposed by Diebold and Yilmaz (2009, 2012, 2015) (DY-method). This approach quantifies how shocks in one market transmit to others over time (Elsayed and Sousa, 2024; Youssef et al., 2021). Furthermore, we also examine directional pairwise spillovers, allowing us to assess the contribution of each market to stablecoin volatility and to evaluate how these effects evolve over time.

This combined framework with TVP-VAR model is particularly well suited to overcoming the limitations of fixed-coefficient VAR models. The TVP–VAR avoids the arbitrary choice of window size, which can produce erratic or flattened parameters. It is also robust to outliers and preserves the full information set when estimating time-varying parameters (Antonakakis and Gabauer, 2017; Antonakakis et al., 2018, 2019; Gabauer and Gupta, 2018; Korobilis and Yilmaz, 2018). These features are especially relevant for volatile assets such as cryptocurrencies, which frequently experience large fluctuations that create outliers in datasets. Finally, we extend the framework to a non-linear specification by decomposing positive and negative price deviations in order to investigate potential asymmetric spillover effects from these markets to stablecoin price deviations.

Our study yields several important findings. First, consistent with earlier work (Hoang and Baur, 2021; Koutsoupakis, 2020; Griffin and Shams, 2020), we find that stablecoin volatility is correlated with, and largely driven by, Bitcoin and Ethereum. Notably, our results extend the literature by showing that volatility is also influenced by the DXY and the S&P 500 index, but not by Ethereum gas prices.

Secondly, we find that volatility spillovers are highly time-varying and dependent on market conditions. Specifically, when external markets experience heightened volatility—for example, during the Covid-19 crisis and the 2022 cryptocurrency crash—the spillover effects intensify. This indicates that a larger share of shocks in these markets is transmitted to stablecoin markets. Such findings also reflect a marked increase in market correlation under extreme conditions, consistent with the notion that financial markets move together more strongly during common events (Bekaert and Harvey, 1995).

Lastly, our analysis reveals asymmetry in the spillover effects on positive and negative price deviations. In particular, volatility in external markets exerts a stronger spillover effects on positive deviations of stablecoin prices than negative ones. This suggest that volatility spillovers and market integration theory (Bekaert and Harvey, 2003; Engle et al.,1990) fit into emerging market such as stablecoin market.

Our contribution is multifold. To the best of our knowledge, this is the first empirical study to analyze the risk transmission and volatility spillovers from external markets, especially non-crypto assets, to stablecoins. We provide new evidence on external drivers of stablecoin volatility and challenge the assumption that stablecoins consistently function as safe havens against cryptocurrencies and traditional assets (Baur and Hoang, 2021; Xie et al., 2021; Feng et al., 2024). Our findings highlight the importance of accounting for spillover effects when designing trading strategies.

Moreover, we extent the spillover framework of Diebold and Yilmaz (2009, 2012, 2015) to decompose pairwise spillover effects and quantify the strength of volatility transmission in each direction (i.e., from external market to stablecoins and vice versa). This allows us to measure the directional spillovers from external markets to stablecoins, revealing the drivers of stablecoins volatility. We address a gap in the literature by emphasizing directional volatility transmission, broadly ignored in studies relying on overall correlations (Antonakakis et al., 2019; Ji et al., 2019).

The remainder of this chapter is structured as follows. Section 2.2 reviews related literature. Section 2.3 summarizes the data used in the analysis. Section 2.4 presents the methodology and models. Section 2.5 reports empirical evidence and robustness tests. Section 2.6 provides discussion, and Section 2.7 concludes.

2. 2. Literature review

Extensive prior research has focused on volatility spillover theory and empirical analysis due to the importance of global financial linkages and the market integration across assets and markets, particularly during periods of uncertainty, such as financial crises and the COVID-19 pandemic. This section will first introduce the development of volatility spillover theory and then review the empirical research on traditional financial markets and cryptocurrency markets. Based on prior literature, we discuss the volatility spillover effects and the phenomenon of spillover asymmetry from both theoretical and empirical perspectives. Additionally, this section outlines the common methodologies used to investigate volatility spillover effects. Finally, this section briefly reviews the literature on stablecoins and the factors influencing them, as well as previous relevant papers on their spillover effects.

2. 2. 1. Spillover Theory

2. 2. 1. 1. Spillover definition

Before the concept of volatility spillover was proposed, the term 'market contagion' was the first terminology to appear in the literature. The word 'contagion' is derived from medicine, referring to the spread of a disease from one person to another, and was later adopted to describe the spread of financial instability across markets (Maaitah, 2020). After 1997, when a currency crisis in Thailand quickly spread throughout Asia and then across the world, the term 'contagion' was used to refer to the spread of financial market turmoil across different markets (Liu and Pan, 1997; Bekaert and Harvey, 2003).

In a boarder definition, financial contagion can be defined as a series of shocks that affect a range of economies at varying degrees, depending on their level of interconnectedness[4]. Since Diebold and Yilmaz (2009, 2012, 2015) defines the spillover index as a measure of market interdependence, the definition of spillover effects becomes clearer. Economists turn to use the more specific terms "shift-contagion" or "pure contagion" to describe the scenario when there is a significant increase in cross-market linkages after a severe market shock (Forbes, 2012). Then combining these concepts, volatility spillover effects refer to the transmission of volatility from one market to another, it can be defined as a measure of the impact of shocks generated in a financial market on other financial markets with full regard to the linkages between these financial assets or markets across the system.

2. 2. 1. 2. Volatility spillover theory

The concept of financial contagion emerged in the context of the ongoing debate surrounding the Efficient Market Hypothesis (EMH). The essence of this theory lies in how financial markets react to the arrival of new information, affecting different markets, assets, or participants in varying ways. According to the EMH, risk can be transmitted from one market to another through the dissemination of new information (Fama, 1970, 1976, 1991). During periods of market turbulence or financial crises, prices adjust rapidly to reflect new information from other markets or assets. This process brings increased volatility, which can be considered a form of volatility spillover.

Ito and Roley (1987) were the first to explore the idea of volatility spillover effect across financial markets, they found a significant linkage between the fluctuations of the Japanese and U.S. exchange markets. Moreover, Engle et al. (1988) proposed two opposite hypotheses: "Heat Waves & Meteor Showers". The Heat Wave hypothesis[5], is also called own spillover hypothesis, this hypothesis indicates an increasing volatility in a certain market does not necessarily increase the volatility in related markets. Heat Wave hypothesis

[4] see Claessens & Forbes (2013)

[5] Heat Wave hypothesis means a hot day in London might keep the weather hot there in the following few days, but this does not necessarily make it hot in Dublin.

actually stresses and describes the auto-correlation phenomenon and has been found to exist in almost all financial markets (Maaitah, 2020). On the contrary, Meteor Shower[6], or cross spillover hypothesis, emphasize the impact on related markets, meaning if a particular shock increases the volatility of one market, the same shock might also intensify the volatility of related markets to some extent.

The volatility spillover theory implies the key aspects of volatility dissemination, which volatility can spread across markets and financial instruments. According to prior literature, there are three main factors that could affect the volatility spillovers between markets. First one is information transmission, which refers to information, such as earnings announcements, geopolitical events, or macroeconomic data, can trigger volatility in one market, and this volatility might spreads to other markets (Jiang et al., 2012; Wang et al., 2021).

Another factor that affects volatility spillovers is market linkage and integration (Bekaert and Harvey, 2003), which could affect the direct spillover effects (Diebold and Yilmaz, 2009, 2012, 2014). Direct spillover effects occur when volatility in one asset or market directly influences another asset or market due to financial linkages. Bekaert and Harvey (2003) points out that markets are highly connected if there is unrestricted capital flow between with equalization of risk-adjusted return. This suggests that any markets with free capital flow would have volatility spillover to each other, and the higher the degree of market integration is, the higher of the cross-market spillover is. Particularly, during periods of uncertainty, the market integration and spillover effects across markets are broadly observed intensified (Liu and Pan, 1997; Beirne et al., 2013; Hung and Vo, 2021), as financial distress transmits from one region or market to another, a phenomenon known as contagion, increasing the market integration (Bekaert and Harvey, 2003). This financial contagion is more frequent and intensified during global economic crises, such as the global financial crisis in 2008 and the outbreak of COVID-19 in 2020, leading to higher financial linkage and spillover effects across markets.

The last factor that might affect volatility spillovers is the behaviors of market participants, which mainly includes institutional tradings and market making tradings. These massive tradings play important roles in volatility transmission, especially during periods of market

[6] Meteor Showers hypothesis means that if meteors fall down to London, Dublin will certainly experience some effects. In other words,

stress. Specifically, institutional traders, such as hedge funds, mutual funds, and pension funds, broadly engage in large buy or sell orders. Their large-scale trading activities and access to sophisticated information and strategies could amplify volatility spillovers as the massive trading activities of institutional investors in cryptocurrency market might lead to herding behavior among other institutional and retail traders (smart money following), especially in high volatility periods (Jalal et al., 2020). When traders in other related markets follow these tradings, volatility then is transmitted from one asset or market to another through the these tradings, this phenomenon is found particularly strong during periods of market stress or uncertainty (Adams et al., 2014). Additionally, market making activities, as an essential part of the market, influence volatility spillovers through their impact on liquidity. During mild periods, market makers significantly contribute to market liquidity and trading volume (Eldor et al., 2006). However, during financial crises or periods of market stress, market makers tend to reduce their activity due to the risk of adverse selection, which will leads to a liquidity crunch (O'Hara, 2003; Anand and Venkataraman, 2016). This reduction in liquidity, on one hand, amplifies price volatility during crises as smaller volume of trades can lead to a larger price impact when market depth is low (O'Hara, 2003), and on the other hand, lead to stronger spillovers in liquidity shortages across markets, thereby strengthening linkage across markets (Sousa and Zaghini, 2008). Moreover, the increased spillover effects during extreme market condition are also caused by traders' behavior of 'Flight to safety' and 'panic selling' (Pericoli and Sbracia, 2003; Bogdan, 2022), the former denotes investors transfer their portfolio into safe-haven assets, the latter means as one market declines, investors in other markets may sell off assets for fear of missing out on early losses.

2. 2. 1. 3. Spillover asymmetry

The presence of asymmetric volatility in financial markets has long been recognized in the literature (Pindyck, 1984; French et al., 1987). Since volatility is transferred across markets via spillovers, it is worth assuming that volatility spillovers exhibit asymmetries as well (Barunik et al., 2016), and therefore the asymmetric volatility spillover in financial markets attracts the interests of researchers. One of the stylized facts associated with financial markets reveals that the financial linkage across markets returns exhibits asymmetries as large negative returns are more correlated than large positive returns (Longin and Solnik, 2001; Ang and Chen, 2002; Youssef et al., 2021; Shahzad et al., 2021).

This phenomenon of asymmetric volatility spillover is mainly due to the financial contagion. According to the above theoretical and empirical studies about volatility spillover and contagion (Bekaert and Harvey, 2003; Forbes, 2012; Shahzad et al., 2021;), financial contagion describes the propagation of financial shocks from one market to others, which broadly occurs during episode of volatility, reflecting a temporary and sharp increase in market linkage and spillover effects. Therefore, due to the financial contagion, volatility spillovers across markets are larger when market is during crisis or huge volatility, and episodes such as crises and market crashes are largely associated with market downturns(Wu, 2001). As a result, volatility spillovers are stronger during market downturns than during upturns.

In addition, during periods of heightened volatility, investors are more sensitive and react more strongly to losses than gains. In other words, large negative return leads to stronger co-movement during during market downturns (Forbes and Rigobon, 2002). Investors also exhibit behaviors such as 'panic selling' and a 'flight to safety' (Pericoli and Sbracia, 2003; Bogdan, 2022), further contributing to the asymmetry between positive and negative return spillovers. Our study contributes to this strand of literature by examining the volatility spillover asymmetry between several external factors and stablecoin deviations.

2. 2. 2. Research strategies and empirical review

To quantify and measure volatility spillovers, two major methodologies have been developed in previous studies: GARCH model and VAR model. These two models are the most commonly used methodologies in volatility spillover analysis (Soriano and Climent, 2005).

GARCH model is derived from the Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982). It provides a useful tool in forecasting financial time series. This model assume that volatility varies over time and is based on past volatility. GARCH (Generalized ARCH) model is proposed by Bollerslev (1986) and Taylor (1986), they extend ARCH model by including lagged values of volatility, allowing for more flexible and realistic modeling of volatility spillovers across different markets. GARCH has been widely used to investigate the volatility transmission across financial markets, including cryptocurrency market (Inagaki, 2007; Bouri et al., 2021; Zhang et al., 2022). GARCH model provides some strong inference in analyzing co-volatilities cases, and it has been developed a series of different extensions such as T-GARCH, E-GARCH and GJR-GARCH addressing different problems in financial data. However, employing all extensions within a single case study becomes increasingly complex. Moreover, using GARCH requires a certain level of correlation among financial variables; otherwise the results might be invalid (Maaitah, 2020). In this regard, researchers have sought to develop a more effective and flexible model to describe the behavior of financial variables in the form of a vector autoregressive (VAR) model.

VAR model was proposed by Sims (1980) to capture the correlation and interdependence amongst different variables within a system. Diebold and Yilmaz (2009) combined this model with variance decomposition and impulse response functions to investigate volatility spillover across markets (DY method). Subsequently, Diebold and Yilmaz (2012, 2015) further improved this method to overcome the ordering problem. Based on a rolling-window VAR model and generalized variance decomposition, the DY method is offering a quantitative assessment of the size and direction of dynamic spillover effects. In DY method, spillover effect is measured with an impulse-response function predicting the impact of an unanticipated shock of one market on others, which is also consistent with the above definition of spillover effects.

Antonakakis and Gabauer (2017) extend the Diebold and Yilmaz (DY) framework by integrating it with a time-varying parameter VAR (TVP-VAR) model, which addresses several limitations of the traditional rolling-window VAR approach. The TVP-VAR method avoids the arbitrary choice of window size, prevents loss of observations when estimating time-varying parameters, and is more robust to outliers (Antonakakis & Gabauer, 2017; Gabauer & Gupta, 2018; Korobilis & Yilmaz, 2018; Antonakakis et al., 2020; Youssef et al., 2021). In this study, we employ the DY–TVP-VAR framework to analyze volatility spillovers between stablecoins and related markets. By further decomposing the pairwise spillover index, we contribute to the literature by providing a more granular perspective on directional spillovers between two assets.

The DY methodology (Diebold & Yilmaz, 2009, 2012, 2015) has been widely applied in empirical research to trace the evolution of market connectedness. Prior studies document significant and time-varying spillovers across a range of asset classes, including equities (Fowowe & Shuaibu, 2016; Shahzad et al., 2018; Zhang et al., 2018), bonds (Louzis, 2015; Ahmad et al., 2018), currencies (Baruník et al., 2016; Singh et al., 2018), commodities (Ji et al., 2019; Zhang & Broadstock, 2018), and interest rates (Louzis, 2015). These findings consistently show that spillovers intensify during financial turmoil, reducing diversification benefits and amplifying systemic risk (Shahzad et al., 2018; Zhang & Broadstock, 2018; Ji et al., 2019). Understanding these dynamics provides insights into how crises propagate and helps identify periods of heightened financial fragility (Billio et al., 2012; Louzis, 2015).

Another well-established result in this literature is that larger markets tend to be net transmitters of volatility to smaller ones. For instance, Candelon et al. (2018) show that shocks from the U.S. equity market strongly influence both developed and emerging stock markets, while Ahmad et al. (2018) report similar patterns in bond markets. Such insights are valuable for regulators concerned with financial stability and for investors seeking to refine portfolio allocation and hedging strategies based on cross-market linkages.

A growing body of research has also examined whether volatility spillovers exhibit asymmetry, with negative shocks transmitting more strongly than positive ones. Evidence of this phenomenon has been found in equities (Shahzad et al., 2021; Youssef et al., 2021), bonds (BenSaïda, 2019), and commodities (Kang et al., 2017). For cryptocurrencies, however, the literature remains limited. Ji et al. (2019) document stronger spillovers through negative returns among major cryptocurrencies, while Cao and Xie (2022) identify asymmetric spillovers between cryptocurrencies and Chinese financial markets. These findings suggest that adverse shocks disproportionately drive cross-market linkages, highlighting the importance of accounting for asymmetry when analyzing volatility transmission in both traditional and digital assets.

2. 2. 3. Cryptocurrency

Based on prior literature on the relationship between cryptocurrencies and traditional assets (see. Corbet et al., 2018; Zeng et al.,2020;), our paper contributes to the literature by investigating the dynamic market integration through volatility spillover between stablecoins and traditional financial markets.

Cryptocurrency is designed as a decentralized peer-to-peer payment system allowing online payments to flow directly from one party to another without a financial institution (Wang et al., 2020). Owing to these attractive characteristics, cryptocurrency, especially Bitcoin, has received much attention after being proposed by Nakamoto (2008). Since 2013, when cryptocurrency was actively traded, Bitcoin – the biggest and most active cryptocurrency has quickly become an important element of global financial market and a new asset class (Corbet et al., 2018; Gajardo et al., 2018).

In the early, the majority of papers in this literature focuses on Bitcoin and its pricing model. Ciaian et al.(2016), Böhme et al. (2015) and Raskin & Yermack (2018) provide a broad perspective on the economics of cryptocurrencies and the blockchain technology they are built upon. Athey et al. (2016), and Pagnotta & Buraschi (2018) propose models of the valuation of digital currencies. Cong et al. (2019) and Easley et al. (2017) study Bitcoin mining fees and the incentives of miners in equilibrium. From 2016, newly introduced cryptocurrencies such as Ethereum, Ripple, Litecoin are gradually cutting into Bitcoin's historically dominant market-value share, and these alt-coins also attracted researchers interests. However, due to the huge volatility (Yermack, 2015), researchers realize that Bitcoin and other cryptocurrencies actually fails to keep their promise as a payment method, and they are more regarded as speculative assets than digital 'fiat money' (Selgin 2015). Since then, a majority of research focus on the volatility of cryptocurrencies, particularly the volatility correlations among different cryptocurrencies, and between cryptocurrencies and traditional assets.

Using VAR method in Diebold and Yilmaz (2009, 2012, 2015), previous research find the connectedness among leading cryptocurrency markets are strong and Bitcoin is at the centre of the connectedness network. Net volatility spillover are transmitted from Bitcoin to altcoins, rather than the opposite direction. Specifically, Moratis (2021) finds that Bitcoin contributes heavily to the spillover risk of the cryptocurrency market. Antonakakis et al. (2019) analyze the connectedness among leading cryptocurrencies, highlighting the role of Bitcoin and Ethereum in the transmission of shocks. Ji et al. (2019) analyze the return volatility connectedness of six leading cryptocurrencies and confirm Bitcoin and Litecoin are at the centre of the network. However, although the spillover effects among leading cryptocurrencies are strong and significant, they are time-varying and largely depending on market conditions. When market experiences heightened volatility, the connectedness tends to intensify (see. Antonakakis et al., 2019; Ji et al., 2019; Katsiampa, 2019; Beneki et al., 2019; Wajdi et al., 2020; Hsu et al., 2021; Kumar et al., 2022). Additionally, the asymmetry connectedness among cryptocurrencies returns has been documented as well. Ji et al. (2019) find the asymmetry connectedness in cryptocurrency returns where spillovers via negative returns are largely stronger than via positive ones.

These high spillover effects among cryptocurrencies indicates that cryptocurrency markets have high degree of integration, and leading cryptocurrencies are highly connected with each other. However, things are different between cryptocurrency market and traditional assets market. The financial linkage between between cryptocurrency market and traditional assets market evolves over time. Before the Covid-19, cryptocurrencies are regarded as a effective hedge against volatility in traditional financial market, while they lost their positions as safe haven of transitional assets.

Since the inception of Bitcoin in 2009, cryptocurrency has long been believed that the cryptocurrency market, has dynamics that is separate from traditional financial markets. Corbet et al. (2018) examine dynamic relationships between three cryptocurrencies and several financial assets, finding cryptocurrency is relative isolated from traditional assets. Zeng et al. (2020) use the VAR model finding the dynamic interconnectedness of returns between Bitcoin and conventional financial assets are weak. Hsu et al. (2021) find cryptocurrencies can be incorporated into financial portfolios for investors who seek optimal dynamic hedging against market turmoil and downwards. These weak connectedness suggests that the financial linkage and market integration between cryptocurrencies and conventional assets are limited, suggesting that cryptocurrencies can serve as a potential diversification option for investors. And research find cryptocurrency could serve as a hedge or safe haven with respect to the traditional financial market such as stock, forex or the commodity market, before and during COVID-19 period (Ji et al., 2018; Urquhart and Zhang, 2019; Wang et al., 2019; Zeng et al., 2020; Hsu et al., 2021).

Nevertheless, after Covid-19, cryptocurrency is more becoming a part of the global financial market and lost its hedge position against transitional assets as the connectedness between cryptocurrency and other assets is observed intensified (Smales, 2021; Al-Shboul et al., 2022; Wątorek et al., 2023). The increasing connectedness between cryptocurrency and traditional financial markets are believed due to the structural change of connectedness in cryptocurrency market evolving in 2020 with monetary injections into cryptocurrency market seeking for safe-haven, bringing higher market synchronization with traditional market (Vidal-Tomás, 2021; Kumar et al., 2022).

2. 2. 4. Stablecoin

Our study also contributes to the literature that focus on stablecoin. Stablecoin is a type of digital currency designed to mitigate high volatility by being pegged to stable assets, such as gold or major fiat currencies like the Euro, Pound, and most commonly, the U.S. dollar (Mita et al., 2019). Stablecoin is a distinct category of cryptocurrency, differing from traditional non-stable cryptocurrencies in their mechanisms, volatility, and using cases. Specifically, in terms of mechanism, Bitcoin and Ethereum are decentralized and not backed by any underlying asset or collateral. The absence of a physical backing or any algorithmic mechanism makes non-stable cryptocurrencies prone to significant fluctuations (Narayanan et al., 2016). However, the design of stablecoins, especially fiat-collateral mechanism, ties them to fiat currencies, makes them more similar to major fiat currencies than speculative assets, thereby granting them higher stability (BIS, 2019; IMF, 2019).

Furthermore, this differences in mechanism bring differences in volatility. Bitcoin and other non-stable cryptocurrencies are much more volatile than equity assets and major fiat currencies (Baur and Dimpfl, 2021), while large stablecoins, especially fully-backed stablecoins, have much less volatility, and are stabler than gold and stock due to the pegging mechanism (Hoang and Baur, 2021). In using cases, the primary purpose of traditional cryptocurrencies are for investment (speculative trading). Catalini & Gans (2020) note that the speculative nature of non-stable cryptocurrencies makes them more suitable for long-term investment rather than day-to-day transactions. On the contrary, stablecoins are regarded as a store of value and medium of exchange in the digital-asset economy due to their high stability (Yermack, 2015), rather than as an alternative investment of traditional assets. Additionally, stablecoins are primarily used to trade non-stable cryptocurrencies (Koutsoupakis, 2020; Hoang and Baur, 2021), and can be used to support and play as a safe haven of non-stable cryptocurrencies (Wang et al., 2020).

Due to the difference in their mechanism, volatility and purpose of usage, stablecoins differ greatly from traditional cryptocurrencies. We therefore argue previous findings on volatility spillovers between non-stable cryptocurrencies and traditional assets cannot be applied to stablecoins. Thus the above brief literature review points out one major research gap, research on financial linkage between stablecoins and traditional assets are ignored in previous literature, which does not match the popularity of stablecoins in trading. Limited papers are mainly focus on connectedness between stablecoins and non-stable cryptocurrencies, potentially overlooking the connectedness between stablecoin and traditional assets. We contribute to this strand of literature by filling this research gap. We firstly investigate the volatility spillover effects between stablecoins and traditional assets, including U.S. Dollar index and S&P 500 index. Furthermore, we expand this stream of literature by identifying the asymmetry of volatility spillovers of stablecoin deviations.

Additionally, due to the higher stability than other non-stable cryptocurrencies, researchers attempt to explore whether stablecoins can serve as a hedge or safe haven against traditional cryptocurrencies. Baur and Hoang (2021) find that stablecoins could be a safe haven against the fluctuation of Bitcoin during specific period. Wang et al (2020) show that stablecoins can serve as safe havens of traditional cryptocurrency, and USD-pegged stablecoins perform better than other type of stablecoins. Xie et al. (2021) claims the safe haven properties of Tether against Bitcoin during the pandemic. Also, very limited studies try to explore the safe haven properties of stablecoins against traditional assets. Feng et al. (2024) find that USD-pegged stablecoins can be considered safe havens against global stock markets, especially during the COVID-19 pandemic period. Our study contributes to this strand of literature by examining the volatility spillover effects between stablecoins and these speculative assets. Our results undermines previous finding that stablecoins could be a safe haven against non-stable cryptocurrency and traditional assets.

2. 2. 5. Potential Drivers of Stablecoin Volatility

2. 2. 5. 1. Non-stable Cryptocurrency

As a vehicle currency in crypto market, stablecoins have been found to be correlated with Bitcoin and other non-stable cryptocurrencies in various ways, including trading volume (Hoang and Baur, 2021), price volatility (Grobys et al., 2021, Kristoufek, 2021;) and market liquidity (Griffin and Shams, 2020). Additionally, as a medium of exchange in cryptocurrency market, stablecoins are also linked to the trading activity of non-stable cryptocurrencies, and thus the fluctuation on price and volume of non-stable cryptocurrencies could affect the demand of stablecoins. Hoang and Baur (2021) and Kristoufek (2021) find stablecoins are largely used to trade leading non-stable cryptocurrencies, with their issuance broadly occurring after non-stable cryptocurrencies gains. Griffin and Shams (2020) find Tether could support Bitcoin's price during market downturns, while Wei (2018) finds that Tether's trading volume increases after Bitcoin's price declines. Baur and Hoang (2021) suggest stablecoins serve as a safe haven with respect to Bitcoin owing to its stability.

The limited research on the spillover effects between non-stable cryptocurrencies and stablecoin focus on the demand of stablecoin caused by non-stable cryptocurrencies. Łęt et al. (2023) find the volatile cryptocurrency market have significant spillover effects to the issuance and circulation of stablecoin shortly, their findings indicate stablecoins are as safe haven assets after bad news in the volatile cryptocurrency market. Kristoufek (2021) analyze the spillover effects between stablecoins issuance and major cryptocurrencies, he finds the increased stablecoins issuances come as reaction to the other cryptoassets price hikes. These significant spillover effects in these research, according to Bekaert and Harvey (2003), indicate the high linkage and integration of cryptocurrencies market and stablecoin market. However, despite the strong linkage between stablecoins and non-stable cryptocurrencies, few studies focuses on the volatility spillover effects between non-stable cryptocurrencies volatility and stablecoins volatility. This paper fills this research gap and contributes to this strand of literature by investigating the volatility spillover effects from leading cryptocurrencies to stablecoins, and the connectedness asymmetry between positive and negative deviations of stablecoins.

2. 2. 5. 2. U. S. Dollar Index (DXY)

The U.S. Dollar Index (DXY) is a measure of the value of the US dollar relative to a basket of six major foreign currencies. It provides a general indication of the strength or weakness of the U.S. dollar in the global market, which is widely used by traders and investors to gauge the performance of the U.S. dollar. The index increases when the U.S. dollar gains value relative to other currencies. The sampled stablecoins in this study are all pegged to U.S. Dollar, and thus DXY could reflect the value or price of the underlying asset of these stablecoins.

Also, according to Bekaert and Harvey (2003), one important feature of markets linkage is unrestricted cash flow between markets. This is the case between stablecoins markets and U.S. dollar market, capital is free to move from one to another, which suggests strong financial linkage between stablecoins market and U.S. Dollar market. One similar case is HongKong dollar and U.S. dollar. HongKong dollar is pegged to U.S. dollar with a fixed rate of 7.8 HKD to 1 USD[7], whose pegging system is similar to that of USD-collateral stablecoins. Previous research found USD and HKD have high financial linkage and market integration due to the pegging design. Volatility of USD could transmit to HKD through swap curve (Huang et al., 2008) and interest rate (Fung and Lam, 2023). Given the similar pegging mechanism between fiat-collateral stablecoins and HKD, we then assume volatility of stablecoin can be impacted by USD, and spillover effects could be observed between these two markets.

Previous studies identify the strong connectedness between DXY and cryptocurrency markets, while most of them focus on non-stable cryptocurrencies (Wang et al., 2022; Lee and Choi, 2024). Overall, according to the market integration theory (Bekaert and Harvey, 2003), we assume the degree of integration between stablecoin markets and DXY market are high as the unrestricted capital flow between, and thus there might be volatility spillover effects from DXY to stablecoin market. We contribute to this literature by identifying the volatility spillover effects between DXY and stablecoin markets.

[7] https://www.bloomberg.com/news/articles/2022-07-31/what-the-hong-kong-dollar-peg-is-and-why-it-matters-quicktake?embedded-checkout=true

2. 2. 5. 3. S&P 500 Index

The S&P 500 index plays a pivotal role in the global financial landscape, exerting significant spillover effects on various markets, including equities, commodities, and foreign exchange (Forbes and Rigobon, 2002; Mensi et al., 2013). In prior research, the interconnectedness of financial markets has been well-documented, with the S&P 500 broadly serving as a leading indicator for market movements across regions (see. Heinlein and Mahadeo; 2023; Qarni and Gulzar, 2018;), and asset classes (Coronado et al., 2018; Hung, 2022; Balcilar et al., 2021).

More recently, as cryptocurrency are more becoming a part of the global financial market (Wątorek et al., 2023), S&P 500 also exhibit strong spillover effects with cryptocurrency markets, particularly leading non-stable cryptocurrencies. Hung (2022) displays strong connectedness between S&P 500 and Bitcoin market, and the connectedness between S&P 500 and cryptocurrency market was observed intensified during Covid-19 period (Lento and Gradojevic, 2021). These significant spillover effects demonstrate strong financial linkage between S&P 500 index and cryptocurrency market. However, despite stablecoins being a key digital currency in the cryptocurrency market, the connectedness between the stablecoins market and the S&P 500 is overlooked. According to the theory of market integration (Bekaert and Harvey, 2003), we believe S&P 500, as a significant driver of global financial volatility, could also transmit volatility spillovers to stablecoin market and drive the stablecoin volatility. We contribute to this body of literature by identifying the volatility spillover effects between S&P 500 and stablecoins markets.

2. 3. Data

We focus on four leading fully collateralized stablecoins – USDT, USDC, TUSD, and USDP – which, as of September 2024, account for over 90% of the total market capitalization and trading volume of the stablecoin market. USDT (Tether) is currently the largest stablecoin by market capitalization and trading volume, maintaining a 1:1 peg to the US dollar. USDC, managed by Circle, is the second largest stablecoin and is backed by cash and short-term US treasuries. TUSD and USDP are also backed by reserves to support their 1:1 USD peg. We collect daily open, high, low, and close (OHLC) price data for these four stablecoins from CoinMarketCap. As a widely used price-tracking platform, CoinMarketCap aggregates stablecoin prices across multiple exchanges using a volume-weighted average, reducing potential price bias arising from exchange selection.

We examine five potential external factors: two leading non-stable cryptocurrencies (Bitcoin and Ethereum), two iconic indices representing traditional assets (the S&P 500 and the DXY), and the gas price of the Ethereum blockchain. Bitcoin and Ethereum are the two largest cryptocurrencies by market capitalization, together accounting for over 70% of the total market and more than half of global trading volume. Their OHLC datasets are also collected from CoinMarketCap. DXY and the S&P 500 are included to capture the influence of the US dollar and the equity market on stablecoin volatility. These datasets are obtained from Investing.com, a leading global financial data provider. Since cryptocurrency trades continuously while the DXY and S&P 500 only trade on weekdays, we exclude weekends and holidays when traditional markets are closed. Gas represents the computational effort required to perform operations on the Ethereum network, with gas prices reflecting transaction costs and network activity levels. Average gas prices are collected from Etherscan.io, a widely used Ethereum blockchain explorer providing data on blocks, smart contracts, wallet addresses, and transactions. To reflect actual transaction costs on Ethereum, we convert gas prices into USD by multiplying the price in Gwei by the corresponding ETH/USD exchange rate. To verify accuracy, we cross-check data against alternative sources: cryptocurrency data from CoinMarketCap is compared with CoinGecko, and DXY and S&P 500 data with Bloomberg. After careful comparison, we confirm consistency across sources, strengthening the reliability of the dataset.

The sample period spans from 1 November 2018 to 31 December 2023, including 1,298 trading days. For relatively young markets such as stablecoins, this five-year period is sufficient long to examine the dynamics of volatility spillovers, encompassing both rapid market development and the evolution of stability (Let et al., 2023). Also, we suggest that a daily dataset is appropriate for this research, as daily data has been widely used in prior studies exploring the correlation between non-stable cryptocurrencies and stablecoins (Griffin and Shams, 2020; Hoang and Baur, 2021; Grobys and Huynh, 2021). Similarly, daily data has been used to study the connectedness between cryptocurrencies and traditional assets as well as stablecoins (Kristoufek, 2021; Elsayed and Sousa, 2024; Let et al., 2023). Our study follows a similar context to these previous works, and daily data are well suited to addressing our research questions.

Following the measure of extreme volatility in Parkinson (1980), Garman & Klass (1980), we calculate the daily volatility as follows,

$$V_t = \sqrt{\frac{(ln(P_{h,t}) - ln(P_{l,t}))^2}{4ln2}} \tag{2.1}$$

where V_t denotes volatility on day t, $P_{h,t}$ and $P_{l,t}$ denotes high and low price on day t respectively.

Given that stablecoin volatility is generally low, we use a measure of extreme volatility to capture daily fluctuations more precisely. In contrast to using GARCH models or realised volatility measures (Hoang and Baur, 2021; Andersen et al., 2003), the Parkinson (1980) extreme volatility measure does not rely on daily returns, most of which may be 0. Specifically, daily returns of stablecoins are highly likely to be zero when calculated from closing or opening prices, since stablecoins are typically priced at USD 1. The extreme volatility measure used here is well suited to stable assets like stablecoins, as it employs daily high and low prices to assess volatility. This allows the measure to capture extreme daily fluctuations and maximum deviations, which is more informative than alternative volatility measures (Parkinson, 1980). In comparison with the daily maximum deviation used in Lyons and Viswanath-Natraj (2023), our approach captures the full range of fluctuations by incorporating both upward and downward volatility. The Parkinson measure has also been applied in Maaitah (2020) to assess volatility spillovers across Bitcoin markets, where it was found to be more efficient than standard close-to-close volatility estimates.

We begin with a descriptive statistical analysis of the dataset. Table 2.1 presents summary statistics for all variables. Due to the unavailability of daily high and low prices for Ethereum gas fees, we use log changes of the average daily price in USD. For all other variables, volatility is calculated using the Parkinson measure (Eq. 2.1). ‘ADF’ denotes the augmented Dickey–Fuller test, used to examine whether a series is stationary, and ‘JB’ denotes the Jarque–Bera test for normality. As shown in Table 2.1, the average volatility of the stablecoins is low and relatively similar across assets, with USDT showing the lowest volatility and USDP the highest. Bitcoin and Ethereum display much higher volatility than stablecoins and other variables, while DXY shows lower volatility than stablecoins. The S&P 500 has higher average volatility than stablecoins but is less volatile than Bitcoin and Ethereum. Gas prices exhibit the lowest average volatility, though with a relatively large standard deviation.

These statistics are consistent with previous findings: while stablecoins are more stable and less volatile than non-stable cryptocurrencies, they are not absolutely stable, as they remain more volatile than fiat currencies (Hoang and Baur, 2021). The ADF tests confirm that all variables are stationary, while the Jarque–Bera tests reject normality. Ljung–Box results further indicate that all variables exhibit autocorrelation.

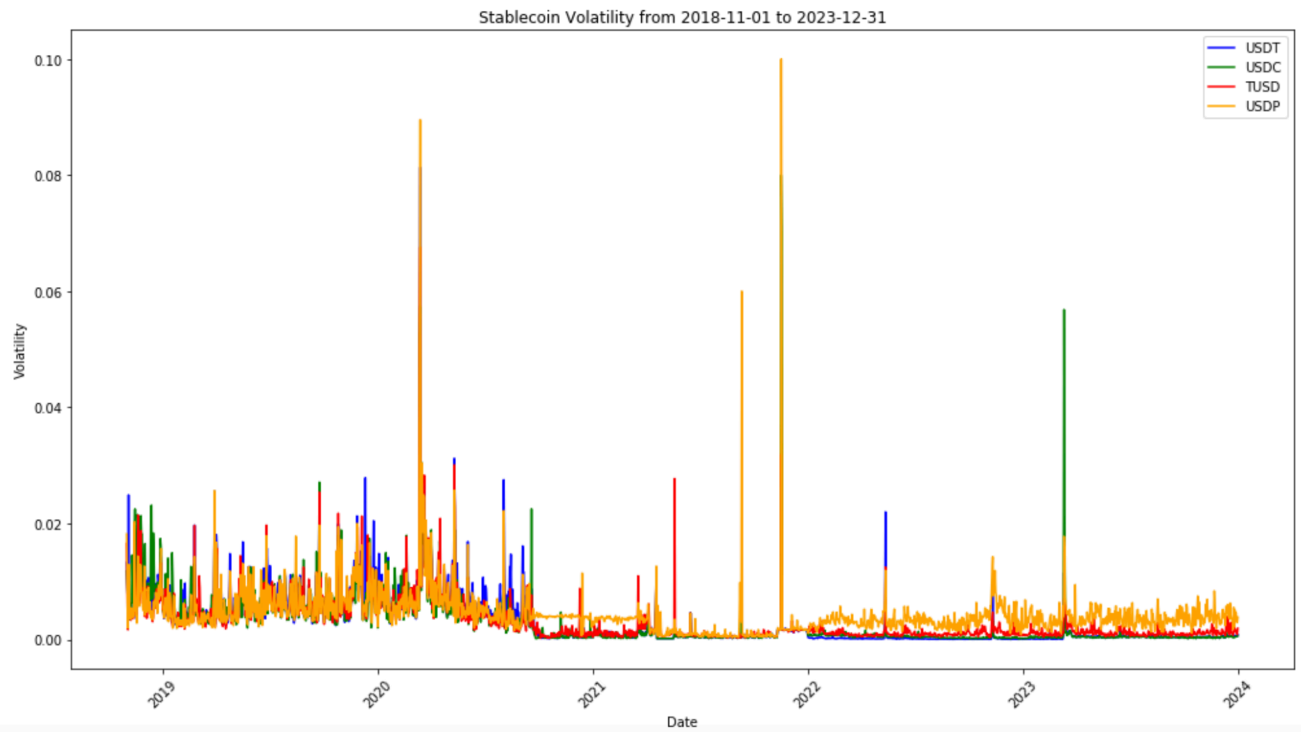
Table 2.1. Descriptive statistics of variables.

	Obs	Mean	SD	ADF	JB	Q(10)
USDT Volatility	1298	0.0042	0.0067	-3.12**	21022***	6611***
USDC Volatility	1298	0.0045	0.0157	-9.16***	95447***	350***
TUSD Volatility	1298	0.0046	0.0061	-2.96**	18265***	5717***
USDP Volatility	1298	0.0069	0.0174	-22.42***	36932***	58***
BTC Volatility	1298	0.0289	0.0221	-6.18***	44559***	1856***
ETH Volatility	1298	0.0363	0.0272	-8.71***	52417***	2103***
DXY Volatility	1298	0.0037	0.0019	-6.49***	3802***	3880***
S&P 500 Volatility	1298	0.0077	0.0056	-6.67***	13337***	7493***
Gas price Volatility	1298	0.0025	0.3178	-10.28***	53456***	211***

This table shows descriptive statistics of stablecoin variables. Gas price volatility is measured as log changes of average daily price while volatility of other variables is estimated by the extreme volatility following Parkinson (1980) as shown in Eq 2.1. Sample period is from 2018-11-01 to 2023-12-31. ADF denotes result of Augmented Dickey–Fuller test. SD denotes deviation and ADF denotes the results of Augmented Dickey Fuller Test. JB is the Jarque-Bera test for normality. Q(10) is the Ljung–Box statistic for autocorrelation in 10 lags. Note: Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

We plot daily volatility of each stablecoin during sample period in Figure 2.1. As can be seen in Figure 2.1, the volatility of each stablecoin is generally low and shows a declining trend, particularly after 2020. Nonetheless, several sharp spikes appear during episodes of market stress. The first occurs in March 2020 during the Covid-19 crisis, likely driven by market panic and large monetary injections into the cryptocurrency market, as investors sought alternative safe-haven assets (Kumar et al., 2022). In May 2021, another spike is observed – especially for TUSD – during a period of heightened cryptocurrency volatility triggered partly by a statement from the People's Bank of China reiterating that digital currencies could not be used for payments in China. Further spikes appear in September and November 2021, both linked to sharp swings in Bitcoin and Ethereum, which later reached record highs. In 2022, two smaller spikes occur, in May and November, associated with the collapse of Terra and FTX, respectively. In March 2023, volatility spikes again, particularly for USDC, after Circle disclosed that nearly 8% of its USD 40 billion reserves were held in the failed Silicon Valley Bank. Thereafter, volatility remains relatively low for all stablecoins through the end of the sample period.

Figure 2.1. Volatility of stablecoin



This figure displays the volatility of four stablecoins. Volatility of stablecoin is estimated by the extreme volatility with daily high price and low price following Parkinson (1980) as shown in Eq 2.1. Sample period is from 2018-11-01 to 2023-12-31.

2. 4. Methodology

Our empirical analysis consists of three steps. We first calculate the Pearson correlations between stablecoin volatility and potential factors. Next, we run a linear regression model of stablecoin volatility on these factors. Finally, we examine the static and dynamic spillover effects between stablecoins and these factors using spillover methods.

2. 4. 1. Correlation and Regression

Firstly, following Solnik et al. (1996), we use Pearson correlation to examine the correlation between volatilities, which is a measure of linear correlation between two random variables (Lee and Nicewander, 1988). It is a ratio between the covariance of two variables and the product of their standard deviations. The calculation is as follows,

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{2.2}$$

where $cov(X,Y)$ is the covariance of X and Y, σ_X and σ_Y are the standard deviation of X and Y, respectively.

Then following Payes (2012) and Hoang & Baur (2021), we use a linear regression model to examine the impact of these factors on stablecoins volatility to identify the potential drivers of stablecoin volatility. The aim of this regression is to investigate the relationship between stablecoin volatility and the volatility of these factors, we use contemporary values of these variables and one lag of stablecoins volatility as control variable to control the autocorrelation of each stablecoin volatility. The linear model is as follows:

$$V_{SC,t} = a_0 + a_1 V_{BTC,t} + a_2 V_{ETH,t} + a_3 V_{DXY,t} + a_4 V_{S\&P500,t} + a_5 V_{Gp,t} + a_6 V_{SC,t-1} + a_7 d_{yearFE} + \epsilon_t \tag{2.3}$$

where V denotes volatility, and d_{yearFE} denotes dummy variables to control year fixed effect, including five dummy variables corresponding to 2019, 2020, 2021, 2022, and 2023, respectively.

Each variable has two subscripts: the first indicates the factor – 'BTC' for Bitcoin, 'ETH' for Ethereum, 'DXY' for the US Dollar Index, 'SP500' for the S&P 500 index, 'Gp' for Ethereum gas prices, and 'SC' for the stablecoin itself. The second subscript denotes time t.

For each stablecoin in our sample, we include its volatility and all external factors in the regression to assess how these factors impact each stablecoin individually. Unlike Hoang and Baur (2021), who use stablecoin trading volume as an independent variable to test whether stablecoins influence Bitcoin volatility, our approach models stablecoin volatility directly as the dependent variable. This allows us to evaluate the combined effects of multiple drivers on stablecoin volatility.

2. 4. 2. Dynamic spillover effects

Then, we turn our attention to volatility spillover effects. In this part we calculate the financial linkage and impacts of these relevant markets on stablecoin volatility through spillover effects, and see how these impacts evolve over time. Diebold and Yilmaz (2009, 2012, 2015) propose a straightforward method of quantifying overall and directional spillovers in the vector autoregressive (VAR) framework (DY method). This method provides a quantitative tool to examine how shocks from one market transmit to others. The DY method is suitable for our studies for several reasons. First, it relies on a Vector Auto-Regression (VAR) approach, which is applied to overcome dimensionality issues. Second, through DY method, dynamic spillover index can be estimated by combined with rolling window method (Gong et al., 2021). The key of the rolling window model is that DY method allows conducting the VAR model estimation under the fixed window length, and get the continuous dynamic spillover index by moving the window period by period. Third, this method allows us to distinguish the effect between the dynamics of *own* shocks and *spillovers* (i) between each stablecoin; (ii) across each stablecoin and each factor; and (iii) between each external factor (Elsayed and Sousa, 2024).

Furthermore, given the nature of high volatility of Bitcoin and other factors, especially during extreme period (see. Yermack, 2015; Baur and Dimpfl, 2021), we assess the dynamic volatility spillovers of potential factors on stablecoins by estimating a Time-Varying Parameter Vector Auto-Regression (TVP-VAR) model, as this framework substantially improves the dynamic performance of the standard VAR model and is not sensitive to outliers (Elsayed and Sousa, 2024).

Specifically, the TVP-VAR is proposed by Koop and Korobilis (2014), which allows the VAR coefficients to vary over time, as such, potential parameter changes are accurately determined. Antonakakis and Gabauer (2017) combined this TVP-VAR model with Diebold and Yilmaz's (2009, 2012, 2015) model, allowing flexible parameters. Therefore, the changeable parameters in the model make it immune to the presence of outliers compared to the spillover approach based on the fixed-coefficient VAR framework. And it overcomes the the drawbacks of fixed-coefficient VAR framework which might have very erratic or flattened parameters. (Antonakakis *et al*., 2020; Youssef et al., 2021). This framework is suitable in our case to catch the fluctuating effect of factors, especially volatile Bitcoin, on stablecoin. This is also a key assumption that adheres to the empirical observation of time-variation in the joint dynamics of models incorporating data similar to ours (Koop and Korobilis, 2014; Youssef et al., 2021; Elsayed and Sousa, 2024). As a result, TVP-VAR can be used in association with the framework put forward by Diebold and Yilmaz (2009, 2012, 2015) to construct spillover indices and examine the dynamic volatility spillovers between related markets and stablecoins.

Following Elsayed and Sousa (2024), the TVP-VAR(p) model with p lags can be written as follows:

$$\boldsymbol{X}_t = \boldsymbol{\Phi}_t \boldsymbol{X}_{t-1} + \boldsymbol{\xi}_t, \quad \boldsymbol{\xi}_t \,|\, \Omega_t \sim N(0, \boldsymbol{\Lambda}_t) \tag{2.4}$$

$$\boldsymbol{\Phi}_t = \boldsymbol{\Phi}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \,|\, \Omega_t \sim N(0, \boldsymbol{\Gamma}_t) \tag{2.5}$$

where $\boldsymbol{X}_t$ is an $N \times 1$ vector of variables, $\boldsymbol{X}_{t-1}$ is an $Np \times 1$ lagged conditional vector, $\boldsymbol{\Phi}_t$ is an $N \times Np$ time-varying coefficient coefficient matrix, $\boldsymbol{\Omega}_t$ is the information set until t and $\boldsymbol{\xi}_t$ is is an $N \times 1$ vector of error disturbance terms with an $N \times N$ time-varying variance-covariance matrix $\boldsymbol{\Lambda}_t$. The parameters matrix $\boldsymbol{\Phi}_t$ depend on their own past values $\boldsymbol{\Phi}_{t-1}$ and an $N \times Np$ error disturbance matrix $\boldsymbol{\eta}_t$ with an $Np \times Np$ variance-covariance matrix.

In our case, $\boldsymbol{X}_t = [\boldsymbol{SC}_t, \boldsymbol{FS}_t]'$, where $\boldsymbol{SC}_t = [USDT_t, USDC_t, TUSD_t, PAX_t]'$ is a vector of stablecoins volatility, $\boldsymbol{FS}_t = [BTC_t, ETH_t, DXY_t, S\,\&\,P500_t]'$is a vector of factors might impact stablecoin volatility, including Bitcoin volatility, Ethereum volatility, U.S. Dollar index volatility and S&P 500 index volatility.

There are two input parameters in this TVP-VAR model, the *H*-step ahead forecast horizon and the lag length, *p*. The *H*-step forecast horizon is set to 10 days, as it could effectively capture the short-term impact of external markets on stablecoins volatility (Elsayed and Sousa, 2024; Antonakakis *et al*., 2020; Youssef et al., 2021). The lag length of the VAR model is decided by the Bayesian information criterion (BIC), which is set to one.

The time-varying coefficients and error covariances are used to estimate the spillover indices of Diebold and Yilmaz (2009, 2012, 2015) through generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) (Koop *et al.,* 1996; Pesaran and Shin., 1998). To calculate the GIRF and GFEVD, we transfer the TVP-VAR model, from formula 2.4 and 2.5, to the vector moving average (VMA) representation as follows:

$$\boldsymbol{X}_t = \boldsymbol{\Phi}_t \boldsymbol{X}_{t-1} + \boldsymbol{\xi}_t = \sum_{i=0}^{\infty} \boldsymbol{A}_{i,t} \boldsymbol{\xi}_{t-i} \tag{2.6}$$

Where $A_{i,t}$ are $N \times N$ parameter matrix where it follows the recursion $A_{i,t} = \Phi_{1,t}A_{i-1,t} + \Phi_{2,t}A_{i-2,t} + \ldots + \Phi_{p,t}A_{i-p,t}$ with $A_{0,t}$ being an identity matrix, and $A_{i,t}$ = 0 for $i < 0$.

The VMA representation is crucial for constructing the impulse-response functions as well as the generalized forecast error variance decompositions (GFEVD). In this framework, the volatility spillovers correspond to fractions of the *H*-step-ahead error variances in forecasting a specific variable *i* of the vector $\boldsymbol{X}_t$ that are due to shocks in variable *j = 1, 2,. . ., N*, such that $j \neq i$, while the own variance shares are fractions of the *H*-step-ahead error variances in forecasting a specific variable *i* of the vector $\boldsymbol{X}_t$ that are due to own shocks, for *i = 1, 2,. . ., N*. And thus it provide precise and specific spillovers from each variable to another, without being interfered by other variables in the system (Elsayed and Sousa, 2024).

The *H*-step ahead forecast error is the difference between the value $\boldsymbol{X}_{t+H}$, and the expectation of value $E_t\boldsymbol{X}_{t+H}$. Similarly, the generalized impulse-response function (GIRF) represents the response of all variables following a shock in variable *i*. Thus, it is the difference between the *H*-step-ahead forecast where variable *i* is shocked by variable j and the H-step-ahead forecast where variable i is not shocked by variable j, which can be expressed as:

$$\mathrm{GIRF}_t(H, a_{j,t}, \boldsymbol{\Omega}_t) = E_t(\boldsymbol{X}_{t+H} \mid \boldsymbol{\xi}_{j,t} = a_{j,t}, \boldsymbol{\Omega}_t) - E_t(X_{t+H} \mid \boldsymbol{\Omega}_t) \tag{2.7}$$

where H represents the forecast horizon and $\boldsymbol{\Omega}_t$ is the information set until t, $a_{j,t}$ is the selection vector to indicate the shocks is from variable j, with one on the j^{th} element and zero for others.

Next, we calculate the generalized H-step-ahead forecast error-variance decomposition (GFEVD), $\lambda_{j,t}(H)$, for $H = 1,2,\ldots$, as:

$$\boldsymbol{\lambda}^{g}_{j,t}(H) = \Lambda^{-\frac{1}{2}}_{jj,t} \boldsymbol{A}_{H,t} \boldsymbol{\Lambda}_t \xi_{j,t} = \frac{\boldsymbol{A}_{H,t} \boldsymbol{\Lambda}_t \xi_{j,t}}{\sqrt{\Lambda_{jj,t}}} \tag{2.8}$$

where $\boldsymbol{\Lambda}_t$ is the N × N time-varying variance-covariance matrix of the vector of error disturbance terms ξ_t, $\sqrt{\Lambda_{jj,t}}$ is the standard deviation of the error term for the j^{th} equation. The GFEVD can be interpreted as the fraction of the variation of other variables that can be explained by a shock to a specific variable (Pesaran and Shin, 1998).

To make the spillover index straightforward, each entry of the variance decomposition matrix is normalized, so that each row sums up to one, that is, all variables jointly explain all of variable's i generalized forecast-error variance. This is calculated as follows

$$\widetilde{\lambda}^{g}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \boldsymbol{\lambda}^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{H-1} \boldsymbol{\lambda}^{2,g}_{ij,t}} \tag{2.9}$$

Where $\sum_{j=1}^{N} \widetilde{\lambda}^{N}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\lambda}^{N}_{ij,t}(H) = N$.

Therefore, the total spillover index can be expressed as:

$$S^{g}(H) = 100 \times \frac{\Sigma^{N}_{i,j=1,i\neq j} \widetilde{\lambda}^{g}_{ij,t}(H)}{N}. \tag{2.10}$$

Furthermore, according to Gabauer (2021), the total spillover index can be decomposed to the pairwise connectedness index measuring the spillover effects between two variables i and j:

$$S_{ji}^{g}(H) = 100 \times 2 \times \frac{\widetilde{\lambda}_{ji}^{g}(H) + \widetilde{\lambda}_{ij}^{g}(H)}{\widetilde{\lambda}_{ji}^{g}(H) + \widetilde{\lambda}_{ii}^{g}(H) + \widetilde{\lambda}_{ij}^{g}(H) + \widetilde{\lambda}_{jj}^{g}(H)} \tag{2.11}$$

However, this metric can only illustrate the degree of bilateral connectedness between variables i and j, which cannot distinguish between the directional pairwise spillover effects from variable i to variable j and the opposite direction. We then further decompose the pairwise connectedness into pairwise directional connectedness to measure pairwise directional spillovers from variable i to variable j:

$$S_{j.i}^{g}(H) = 100 \times 2 \times \frac{\widetilde{\lambda}_{ji}^{g}(H)}{\widetilde{\lambda}_{ji}^{g}(H) + \widetilde{\lambda}_{ii}^{g}(H)} \tag{2.12}$$

The coefficient 2 makes $S_{j.i}^{g}(H)$ range between [0,1], the closer the values get to 1 the stronger market shock could transmit from i to j. The directional pairwise spillovers represent the ratio of the spillover index from variable i to variable j relative to the sum of the spillover index from variable i to itself and from variable i to j.

This framework provides straightforward measures of both total connectedness across the entire system and directional pairwise connectedness between variables, thus enabling us to investigate dynamic connectedness between each stablecoin and each external markets under different market conditions.

2. 5. Empirical result

2. 5. 1. Results of correlation and regression

In this section, we display the results of our data analysis. We start by showing the Pearson correlation between stablecoins and these factors. The results of Pearson correlation are displayed in Table 2.2. As can be seen in Table 2.2, it turns out that stablecoins are highly correlated with each other, and they are significantly correlated with most factors except gas price. The external markets we investigate also display high correlation with each other.

Table 2.2. Correlation between stablecoin volatility and factors.

	USDT	USDC	TUSD	USDP	BTC	ETH	DXY	S&P 500	Gas
USDT	1	0.425***	0.821***	0.323***	0.336***	0.2294***	0.013	0.264***	0.021
USDC		1	0.518***	0.718***	0.151***	0.164***	0.004	0.073***	0.021
TUSD			1	0.414***	0.381***	0.344***	0.02*	0.227***	0.008
USDP				1	0.162***	0.169***	0.042**	0.081***	0.006
BTC					1	0.849***	0.039*	0.135***	0.176***
ETH						1	0.033	0.143***	0.177***
DXY							1	0.502***	-0.038
S&P 500								1	-0.050*
Gas									1

Table 2.2 shows Pearson correlation coefficients among all variables. Gas price volatility is measured as log changes of average daily price while volatility of other variables is estimated by the extreme volatility following Parkinson (1980) as shown in Eq 2.1. Sample period is from 2018-11-01 to 2023-12-31. Note: Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Specifically, as can be seen in Table 2.2, it shows strong and positive and strong correlation among volatility of stablecoins, which ranges between 0.323 (between USDT and USDP) and 0.821 (between USDT & TUSD). These high correlation coefficients confirm the strong and positive relationships among the volatilities of fully backed stablecoins, indicating that the volatility of one stablecoin could affect another. Strong correlations between stablecoins might also be one reason for excess volatility in stablecoin markets.

Furthermore, between stablecoins and these factors, most coefficients are significant except gas prices. Bitcoin and Ethereum both exhibit significant and positive correlations with stablecoins, suggesting that the volatility of leading cryptocurrencies is positively associated with stablecoin deviations. These high correlations in volatility are consistent with the fact that stablecoins are primarily used to trade non-stable cryptocurrencies (Hoang and Baur, 2021; Kristoufek, 2022) and to support the prices of non-stable cryptocurrencies (Griffin and Shams, 2020; Wei, 2018). Stablecoins are also positively correlated with the S&P 500. These significant correlations between the S&P 500 and stablecoins indicate that the two asset classes share common demand and volatility dynamics, offering limited diversification when held together. These results are inconsistent with previous trading strategies that assumed stablecoins were not correlated with the global stock market and could therefore be regarded as safe havens (Feng et al., 2024; Paeng et al., 2024).

DXY shows weak correlations with stablecoins. The correlations between TUSD and USDP with DXY are relatively small but significant, while the correlations between USDT and USDC with DXY are insignificant. Gas price volatility does not show any significant correlation with stablecoins. These results indicate that DXY might have a slight correlation with stablecoins, while gas prices have no impact on stablecoin volatility.

Table 2.3 presents the results of Equation 2.3, which examines the relationships between stablecoins and external factors using the linear regression model. The results further suggest that the volatilities of Bitcoin, Ethereum, and the S&P 500 are positively connected with stablecoin volatility, while DXY shows only a weak connection with TUSD volatility. The coefficients for gas prices are not statistically significant.

Table 2.3. Results of Regression.

	USDT	USDC	TUSD	USDP
$V_{BTC,t}$	0.200** (0.096)	-0.002 (0.055)	0.217** (0.098)	0.007 (0.083)
$V_{ETH,t}$	0.043 (0.047)	0.061** (0.039)	0.103*** (0.019)	0.083 (0.057)
$V_{DXY,t}$	-0.007 (0.016)	0.006 (0.009)	0.011** (0.020)	0.004 (0.006)
$V_{S\&P\ 500,t}$	0.042** (0.021)	0.011 (0.010)	0.062** (0.029)	0.025* (0.013)
$V_{Gp,t}$	0.047 (0.051)	-0.008 (0.013)	0.077 (0.055)	-0.028 (0.036)
$V_{SC,t-1}$	0.469*** (0.062)	0.208*** (0.028)	0.424*** (0.070)	0.110*** (0.028)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	1297	1297	1297	1297
Adjusted R-squared	0.685	0.130	0.652	0.062
Clustered SE	Year	Year	Year	Year

Table 2.3 presents the result of equation 3, where volatility of Bitcoin, Ethereum, DXY, S&P 500 and Gas price are regressed on each stablecoin volatility. Each column represents the result of the regression one stablecoin. Sample period is from 2018-11-01 to 2023-12-31. All regressions include year fixed effects. Standard errors clustered by year in parentheses. No multicollinearity between these variables is detected through VIF test. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

As can be seen in Table 2.3, after controlling for year fixed effects, USDT and TUSD volatilities respond strongly to Bitcoin market volatility, while USDC volatility reacts more to Ethereum market volatility. DXY has a relatively weak impact on stablecoins, with a significant coefficient only for TUSD. However, the S&P 500 shows significant coefficients for USDT, TUSD, and USDP. This indicates that stablecoins can be impacted by some of the market-wide risk when equities fluctuate, but the strength of that linkage varies by coin. USDT and TUSD traders appear to react more to broad traditional market stress than USDC or USDP users. Moreover, the significant coefficients of volatility on the previous day show the high persistence of stablecoin volatility, indicating that yesterday's volatility is the strongest predictor of today's – a common feature in high-frequency financial series.

Based on the results presented in Table 2.2 and Table 2.3, it is suggested that BTC volatility, ETH volatility, DXY volatility, and S&P 500 volatility could significantly impact stablecoin volatility, while gas price has no significant influence on stablecoin volatility. Our analysis is robust. We examined the potential multicollinearity between these factors using the Variance Inflation Factor (VIF) test and detected no multicollinearity. We also included lagged stablecoin volatility in the regression to control for autocorrelation.

Overall, the correlation and regression analysis indicate that stablecoin volatility is correlated with related external markets, including non-stable cryptocurrencies and traditional equity and currency markets. Our findings indicate that stablecoin volatility is driven by non-stable cryptocurrency markets and major traditional financial markets, which contradicts previous claims that stablecoins could be viewed as safe havens due to their independence from traditional cryptocurrency markets and global stock markets (Wang et al., 2020; Xie et al., 2021; Feng et al., 2024; Paeng et al., 2024).

2. 5. 2. Static Volatility Connectedness

We now turn to the volatility connectedness among stablecoins and external factors to measure the impact and investigate how the impact of these factors on stablecoins volatility evolves over time. Since gas prices showed no significant relationship with stablecoin volatility in the previous analysis, they are excluded in this section. We start by calculating the average volatility spillovers between the four factors and stablecoins over the full sample period. Specifically, following the connectedness approach of Diebold and Yilmaz (2009, 2012, 2015) and Antonakakis and Gabauer (2017), we employ the TVP–VAR model developed by Koop and Korobilis (2014) to calculate the average spillover indices. The results are presented in Table 2.4.

Table 2.4 presents the matrix of static volatility spillovers among four related markets and stablecoins during the whole sample period, showing the spillovers among variables. Additionally, it reports the directional volatility spillovers from each variable to all others ('To others') and from all others to each variable ('From others'). Table 2.4 also reports the net directional spillover ('Net'), which is the difference between the spillovers received from other variables and those transmitted to others. A positive (negative) net spillover value indicates that the corresponding variable is a net transmitter (receiver) of volatility spillovers in the system.

Each row represents the spillovers received by a variable from itself and others. These values are expressed as percentages, where the total spillovers received by each variable, including both self-induced and external spillovers, sum to 100%. In other words, each row in the spillover matrix sums to 100%. For example, the second row of Table 2.4 shows the spillovers that USDT receives from each variable. USDT receives 28.69% of its spillovers from itself, with the remaining 69.67% from other variables, including 13.38% from USDC and 21.86% from TUSD. Each column, in turn, shows the spillovers transmitted by a variable to others. For instance, the second column shows the spillovers that USDT transmits: 19.44% to USDC and 23.43% to TUSD. The diagonal values represent self-induced spillovers.

Table 2.4. The static volatility spillovers.

	USDT	USDC	TUSD	USDP	BTC	ETH	DXY	S&P 500	FROM others
USDT	28.69	13.38	21.86	15.65	5.58	4.01	6.12	4.72	71.31
USDC	19.44	29.39	16.95	17.43	5.03	4.02	4.07	3.67	70.61
TUSD	23.43	12.25	26.39	17.34	5.54	3.86	6.36	4.83	73.61
USDP	17.98	15.60	19.42	28.61	5.69	3.62	4.78	4.30	71.39
BTC	9.86	6.45	9.96	8.57	34.37	23.73	3.19	3.87	65.63
ETH	10.30	6.51	10.13	7.60	24.24	33.04	3.27	4.90	66.96
DXY	9.03	4.50	10.16	6.43	2.84	2.13	50.19	14.73	49.81
S&P 500	9.54	5.07	9.82	7.68	4.03	4.20	12.47	47.18	52.82
TO others	99.58	63.76	98.30	80.70	52.95	45.57	40.27	41.02	522.14
NET spillovers	28.27	-6.85	24.69	9.31	-12.68	-21.40	-9.55	-11.80	TSI = 65.27%

Table 2.4 demonstrates the results of static volatility spillovers among stablecoins and external factors including volatility of Bitcoin, Ethereum, DXY and S&P 500 throughout the full sample period. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1. The values are percentages. Each column denotes the spillovers that factor in the first row in this column transmits to each variable, each row denotes the spillovers that factor in the first column receives from each variable. The values are the percentage of volatility spillover and the sum of each row is 100. The total spillover index, which appears in the lower right corner of the table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

Table 2.4 shows strong connectedness among stablecoins and external factors. The total spillover index (TSI) is 65.27%, meaning that, on average, 65.27% of the forecast error variance for all variables originates from other variables. This suggests strong connectedness and substantial volatility spillover effects among these variables. The TSI of 65.27% is the average of three parts of spillovers: (i) volatility spillovers between external markets and stablecoins, (ii) volatility spillovers among stablecoins and (iii) spillovers among external markets.

First, table 2.4 presents volatility spillovers from external markets to stablecoins, where it ranges from 3.62% to 6.36%, indicating the shocks from related markets could transmit to stablecoins market and increasing its volatility. Our results show that when volatility increases in these related markets, stablecoins markets would react to it and thus being more fluctuated. The spillover effects contradicts previous literature that stablecoins market is independent from non-stable cryptocurrencies and traditional global markets (Wang et al., 2020; Xie et al., 2021; Feng et al., 2024; Paeng et al., 2024).

Moreover, row two to five show the spillovers that stablecoins receive from each other, highlighting a strong connectedness among the four stablecoins. For example, USDT receives between 13.38% and 21.86% of spillovers from other three stablecoins. This demonstrates that stablecoins could also significantly influence each other's volatility. Also, combined with the results of correlations, it turns out stablecoins could strongly impact each other and share common demand and fluctuation dynamics.

Also, we note that stablecoins exhibit a strong spillover effects to related external markets, in some cases greater than those received from them. For example, Bitcoin receives spillovers from stablecoins ranging from 6.45% to 9.96%. This may be because stablecoins are widely used to trade and support the prices of non-stable cryptocurrencies (Griffin and Shams, 2020; Kristoufek, 2021). Moreover, increased demand for stablecoins following gains in traditional assets can lead to new issuance, further boosting Bitcoin's price by reflecting heightened demand for cryptoassets (Kristoufek, 2022; Let et al., 2023). Thus, though the spillover results show that stablecoins could transmit strong spillovers to Bitcoin and Ethereum, as speculative drivers, we believe the volatility of Bitcoin and Ethereum are necessary impacted by stablecoins. This phenomenon could due to the delayed transmission of volatility spillovers, where volatility takes longer to transmit across markets, which could create a feedback loop and heightened volatility in stablecoins market would lead to increased volatility in Bitcoin and Ethereum markets in return.

Table 2.4 also demonstrates high connectedness among these external markets, indicating a high financial linkage between them. Specifically, Bitcoin and Ehereum received high spillovers from each other, DXY and S&P 500 also shows high connectedness with each other.

Overall, results in this part show that: (i) stablecoins have strong connectedness among each other; (ii) stablecoins could be impacted by each other and related markets; (iii) the spillovers among related markets are significant. The result in this part suggests that stablecoins receive significant volatility spillovers and thus impacted by Bitcoin, Ethereum, DXY and S&P 500, indicate strong financial linkage and market integration between stablecoins and these markets.

Although stablecoins appear as net transmitters of volatility spillovers in the system, while external factors act as net receivers, this does not necessarily imply that stablecoins drive external markets. Two reasons support this view. First, the majority of volatility spillovers from stablecoins go to other stablecoins due to their high correlations. Second, as anchored assets, stablecoins are less likely to significantly impact speculative assets such as non-stable cryptocurrencies or traditional financial markets (Grobys et al., 2021).

To further verify the direction volatility transmission between stablecoin and these speculative drivers, we conduct a Granger causality test to verify if stablecoins could actually impact the volatility of these related markets. Granger causality test has been wildly used to analyze relationships in cryptocurrency markets (see Balcilar et al., 2017; Bouri et al., 2019; Yarovaya and Zieba, 2022).

Following Diks and Panchenko (2006), for a stationary bivariate time series process $\{(X_t, Y_t)\}$, t □ Z, $\{X_t\}$ is a Granger cause of $\{Y_t\}$ if, for some $k \geq 1$,

$$(Y_{t+1}, \ldots, Y_{t+k}) \,|\, (F_{X,t}, F_{Y,t}) \nsim (Y_{t+1}, \ldots, Y_{t+k}) \,|\, F_{Y,t}$$

where $F_{X,t}$ and $F_{Y,t}$ denote the information contained in past observations of X and Y, respectively, and "~" denotes fitting into equivalent distribution (Granger, 1969).

In other words, if past and present values of X could provide extra explanation power about future values of Y, which are not contained in the past and present values of Y, we say $\{X_t\}$ is a Granger cause of $\{Y_t\}$. And the null hypothesis is that X is not a granger cause of Y, if the p-value of statistics is small enough, we could say X is a granger cause of Y. The results of Granger causality test of are shown in table 2.5.

Table 2.5. Granger causality test between stablecoin markets and related markets.

	USDT	USDC	TUSD	USDP	BTC	ETH	DXY	S&P 500
USDT					0.031***	0.098***	0.081***	2.107**
USDC					0.081	0.584	0.082	2.261**
TUSD					5.350***	6.882***	0.353**	4.062***
USDP					2.547**	1.612*	1.501*	3.371***
BTC	1.751*	0.302	1.832	0.647				
ETH	3.928**	1.469	3.49**	2.611*				
DXY	0.714	0.369	0.150	0.013				
S&P 500	3.147*	0.228	0.251	0.151				

This table display the results of Granger causality between stablecoin markets and related markets. Values in right and upper part are Granger causality results from volatility of related markets to stablecoins volatility. Values in left and lower part are Granger causality results from stablecoins volatility to volatility of related markets. Note: Significant at 0.001 '***', 0.01 '**', 0.05 '*'.

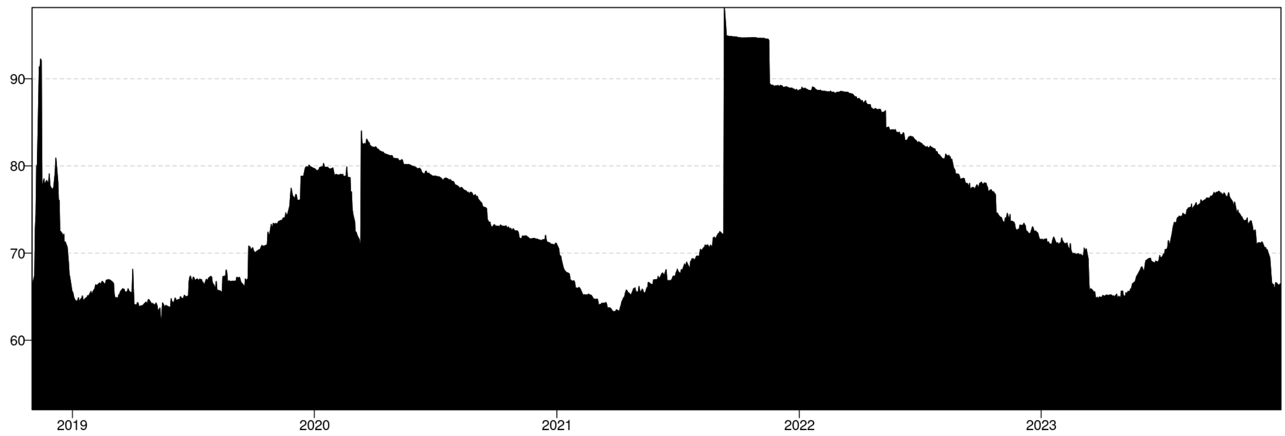
Table 2.5 shows the results of Granger causality test, which show strong unidirectional causality running from Bitcoin, Ethereum, the U.S. dollar index (DXY), and the S&P 500 to stablecoin markets, suggest that stablecoins are primarily responsive rather than driving assets in this financial ecosystem. In other words, stablecoin dynamics do not appear to drive price movements in major crypto or traditional financial markets; instead, they adjust in response to shocks originating in those markets. These results indicate that stablecoins are more driven by speculative drivers, representing by the related markets, instead of the opposite way, even though the spillovers from stablecoin to these related markets are significant.

2. 5. 3. Dynamic Volatility Connectedness

This section employs the DY method and its rolling window to examine the dynamic total connectedness among stablecoin volatility and external factors, investigating how market connectedness and spillover effects evolve over time. The time-varying connectedness index is derived from the generalized forecast-error variance decomposition (GFEVD) based on the TVP–VAR model. Figure 2.2 presents the dynamic total spillover index, showing that total spillover effects are strong and highly time-varying across the sample period. Connectedness between stablecoins and external markets tends to intensify during episodes of extreme market conditions.

The total spillover index (TSI) in Figure 2.2 exhibits substantial time variation, with three notable spikes aligning with periods of heightened volatility in stablecoin markets. The first spike (Nov-Dec 2018) coincides with the cryptocurrency crash, when Bitcoin lost nearly one-third of its value in a week and Ethereum fell to around $84. After this, the total connectedness drops to under 70% and then keeps relatively stable until the outbreak of Covid-19.

Figure 2.2. Dynamic Total spillover effects.



This Figure displays the time-varying dynamics of total spillover index among stablecoin and four external factors, including Bitcoin, Ethereum, DXY and S&P 500. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1. The values on vertical axis are percentages.

The second spike occurred in March 2020 during the COVID-19 outbreak, when global financial panic and unprecedented monetary interventions triggered sharp declines in both cryptocurrency and stock markets, consistent with structural changes in market integration documented by prior studies (see. Smales, 2021; Kumar et al., 2022; Al-Shboul et al., 2022). The increase of market integration is possibly because the financial panic spread among all the markets as a consequence of the impact of COVID-19 (Vidal-Tomás, 2021). After this volatile period, the total spillovers gradually decrease to about 60% and then goes back to 70% in October 2021.

The third spike emerged in late 2021, when spillovers exceeded 90% amid extreme price swings that pushed Bitcoin and Ethereum to historical highs. A smaller surge is also observed in mid-2023, corresponding to volatility in the U.S. stock market as the S&P 500 peaked before sharply declining.

The dynamic total spillover index indicates that the market integration between stablecoins and related markets are strong, implying high transmission of shocks among these markets. Specially, it shows that connectedness among stablecoins and related markets is largely time-varying and intensified during episode of volatility. The results indicate that markets integration and financial linkage between stablecoins and these markets are dominated by market conditions, with spillover effects tending to intensify during periods of heightened market volatility. Our findings suggest the financial contagion and market integration theory could be applied in stablecoin markets (Liu and Pan, 1997; Bekaert and Harvey, 2003; Beirne et al., 2013; Hung and Vo, 2021).

So far, we have identified the total dynamic volatility spillover effects between stablecoins and these factors are at high level and time-varying. We now turn to the directional pairwise connectedness to investigate how the spillover effects from each factor to each stablecoin evolves over time. As noted earlier, pairwise spillovers lie within the range [0, 1], with higher values reflecting stronger connections.

Figure 2.3 shows the dynamic directional pairwise volatility spillovers from Bitcoin and Ethereum to stablecoins, which are strong, time-varying, and exhibit three major spikes corresponding to the cryptocurrency crash in December 2018, the COVID-19 outbreak in March 2020, and the surge in volatility as Bitcoin and Ethereum reached new highs between September and November 2021. These patterns align with periods of elevated stablecoin volatility in Figure 2.1. A smaller spike appears in May 2021—particularly for TUSD—following Tesla's suspension of Bitcoin payments and renewed restrictions on digital currency use in China[8].

[8] https://en.wikipedia.org/wiki/Cryptocurrency_bubble

Fig 2.3. Dynamic directional pairwise volatility spillovers from Bitcoin, Ethereum to stablecoins.

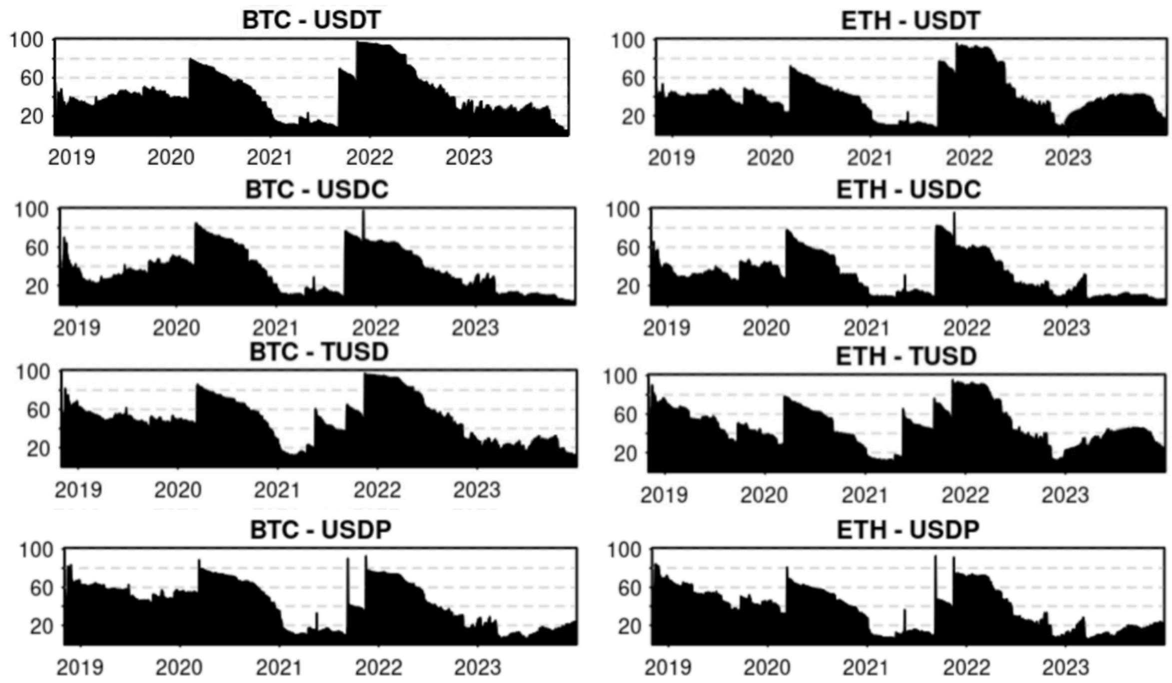


Figure 2.3 presents the dynamic pairwise directional spillovers from Bitcoin and Ethereum to each stablecoin. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1.The values on the vertical axis are percentages.

Overall, the results show that major traditional cryptocurrencies largely drive stablecoin volatility, with their effects evolving over time and tending to intensify during episodes of market stress. The spillover effects from Bitcoin and Ethereum to each stablecoin are strongly time-varying and increase during extreme conditions in the cryptocurrency market. Furthermore, the financial linkages between stablecoins and traditional cryptocurrencies are amplified when the latter are in turmoil. These results partly answer our research questions, confirming that Bitcoin and Ethereum are two key drivers of stablecoins, and that their impact is time-varying and heightened during periods of uncertainty. This finding challenges prior claims that stablecoins are relatively independent of other cryptocurrencies (Wang et al., 2020; Baur and Hoang, 2021; Xie et al., 2021).

The dynamic directional pairwise spillovers from DXY and S&P 500 to each stablecoin is presented in Figure 2.4. The results indicate that the directional pairwise volatility spillovers from DXY and S&P 500 to stablecoins exhibit a largely time-varying picture.

In Figure 2.4, the directional pairwise spillovers transmitted from DXY to each stablecoin are weaker than those from non-stable cryptocurrencies to stablecoins. While they remain below 10% for most of the sample period, two major spikes are evident in the plots. Initially, the spillovers from DXY to stablecoins are relative low and stable until March 2020. The first spike then occurs in March 2020, with spillovers reaching around 20%. This elevated level persists until October 2020, a period characterised by significant uncertainty in DXY due to the panic surrounding COVID-19. Another spike arises in October 2022, when the spillovers from DXY to stablecoins again approach 20%. At that time, the DXY rose sharply, reaching its highest level in 20 years. After March 2023, the spillovers from DXY to stablecoins decrease and remain low and stable until the end of the sample.

Fig 2.4. Dynamic directional pairwise volatility spillovers from DXY and S&P 500 to stablecoins

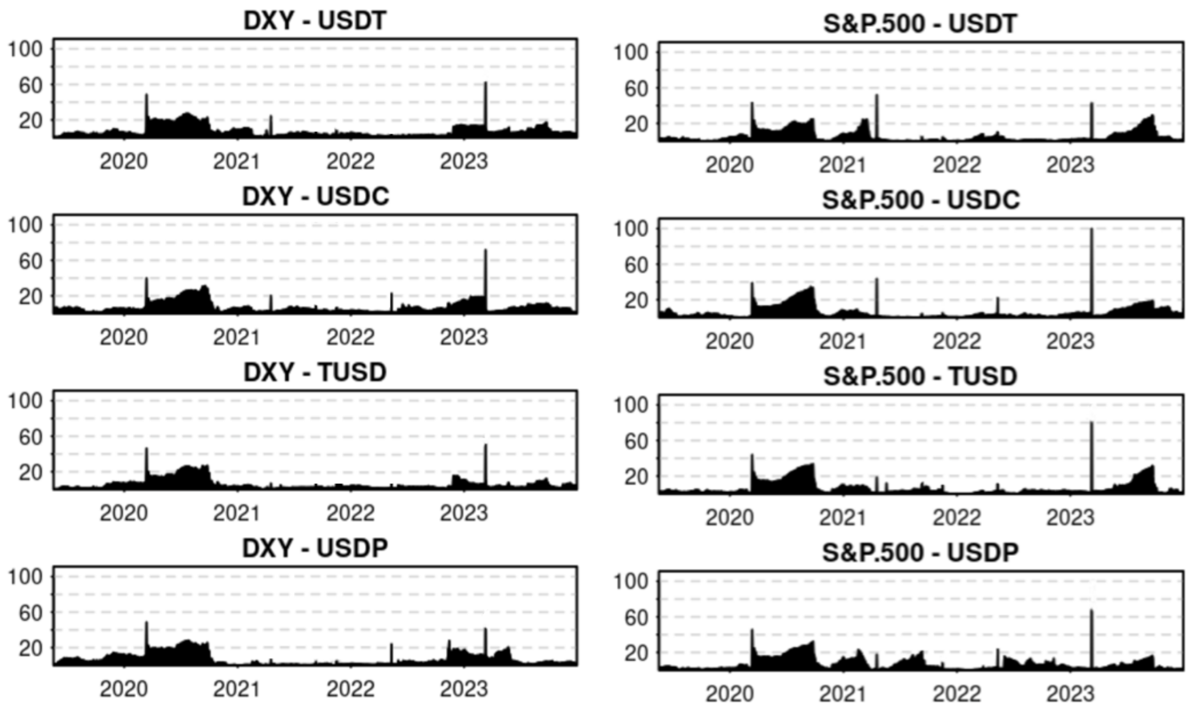


Figure 2.4 presents the dynamic pairwise directional spillovers from DXY and S&P 500 to each stablecoin. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1.The values on the vertical axis are percentages.

Furthermore, as can be seen in Figure 2.4, the directional pairwise spillovers from the S&P 500 to stablecoins are also strongly time-varying. Although generally low, two notable spikes appear during the sample period. The first occurs in March 2020, coinciding with the onset of the Covid-19 pandemic, which caused extreme fluctuations and a sharp decline in the S&P 500. Another spike is observed in mid-2023, corresponding to heightened volatility in the index between June and August, when it reached its annual peak before declining. Overall, the spillovers from DXY and the S&P 500 to stablecoins vary with market conditions, and the intensified transmission during turbulent periods indicates that stablecoins are unlikely to serve as safe havens against traditional assets when volatility is high.

The results of total connectedness and directional pairwise volatility spillovers suggest that the relationships between stablecoins and their volatility drivers fluctuate considerably and are highly dependent on market conditions. During extreme events, such as the cryptocurrency crash or the outbreak of Covid-19, spillovers from Bitcoin and Ethereum to stablecoins increased substantially, indicating stronger integration between them. Similarly, when DXY experienced heightened volatility—such as between March and October 2020, or in September 2022 when it reached a 20-year high—the spillovers from DXY to stablecoins intensified, suggesting closer financial linkages. The S&P 500 also transmitted higher spillovers to stablecoins during periods of market stress, notably in March 2020 and mid-2023.

The intensification of spillover effects and market connectedness during periods of heightened volatility can be attributed to several reasons. First, heightened volatility often leads to financial contagion effect, which can amplify the connectedness and integration across various financial markets (Liu and Pan, 1997; Bekaert and Harvey, 2003; Trabelsi, 2019). During uncertainty, the panic will spread during heightened volatility (Vidal-Tomás, 2021), therefore investors are seeking for safe haven or other alternative investment, which brings more frequent capital flow and thus increases the market synchronization and connection of different market (Vidal-Tomás, 2021; Kumar et al., 2022; Al-Shboul et al., 2022). Second, the nature of volatility itself plays a crucial role in this the time-varying connectedness. Zhang and Hamori (2021) noted that volatility spillovers are more pronounced at lower frequencies, indicating that volatility takes longer to transmit across markets. This delayed transmission can create a feedback loop where heightened volatility in one market leads to increased volatility in connected markets, thereby intensifying overall market connectedness. Finally, macroeconomic factors and policy responses during periods of volatility can also exacerbate spillover effects. K and Mishra (2023) highlighted that macroeconomic policies broadly serve as triggers for volatility transmissions, indicating that the interconnectedness of markets can be influenced by external economic conditions. Elsayed and Sousa (2021) also find the connectedness between interest rates and cryptocurrency market is intensified when central banks put forward large-scale non-standard monetary policies. This is particularly relevant during crises when coordinated policy responses, such as The Federal Reserve adjusted interest rates, may lead to synchronized movements across markets.

Figure 2.4 shows the dynamic directional pairwise spillovers from DXY and S&P 500 to each stablecoin are largely time varying and tend to increase during extreme conditions of cryptocurrency market. The results indicate that the financial linkage between stablecoins and traditional equity and currency market are intensified when markets are in turmoil period. These results answer the rest of our research question, demonstrating that DXY and S&P 500 are two drivers of stablecoins, and their effect on stablecoins volatility tend to increase during episode of uncertainty. The finding undermines the findings in literature that the volatility of stablecoins are independent from global stock market (Feng et al., 2024).

Overall, the evidence shows that spillovers from major cryptocurrencies, as well as from equity and currency markets, intensify during turbulent periods. This suggests that shocks in these drivers can easily transmit to stablecoin markets during crises. Our results therefore challenge the view that stablecoins can serve as safe havens for either cryptocurrencies or traditional assets (Wang et al., 2020; Baur and Hoang, 2021; Xie et al., 2021; Feng et al., 2024). Furthermore, consistent with prior spillover research, we expect asymmetric effects—where negative returns are more strongly linked than positive ones, given their association with periods of stress. The next section examines asymmetric connectedness in stablecoin markets.

2. 5. 4. Asymmetric connectedness results

To provide more detailed insights into dynamic connectedness, we extend our analysis to a framework that tests whether spillover effects differ across positive and negative stablecoin peg deviations. Maximum deviation is defined as the largest deviation of a stablecoin's price from its peg (Lyons and Viswanath-Natraj, 2023). If the price at which the maximum deviation occurs is higher than the peg, the deviation is positive; otherwise, it is negative. We separate daily maximum deviations of stablecoins into positive and negative series and re-estimate the dynamic spillovers between the stablecoins and external factors. Following Youssef et al. (2021), the positive and negative maximum deviations are defined as follows:

$$D_t^+ = Max(D_t, 0) \tag{2.15}$$

$$D_t^- = Min(D_t, 0) \tag{2.16}$$

and thus,

$$D_t = D_t^+ + D_t^- \tag{2.17}$$

where D_t denotes the max deviation of stablecoins at time t, D_t^+ and D_t^- denote the positive and negative maximum deviation at time t, respectively. This approach allows us to distinguish the dynamic connectedness of the positive deviations from the negative deviations (Youssef et al., 2021).

Table 2.6 summarizes the averaged volatility spillover indices between the positive maximum deviation of stablecoins with factors including Bitcoin, Ethereum, DXY and the S&P 500, while Table 2.7 presents the results of the averaged spillover indices between negative maximum deviation of stablecoin and external markets. As can be seen in Table 2.6 and Table 2.7, the total spillovers index (TSI) for the positive maximum deviations (65.14%) was higher than that for the negative maximum deviations (54.72%), indicating that spillover effects of positive deviations have more substantial magnitudes than negative ones.

Looking at the 'From others' column in Tables 2.6 and 2.7, we observe that positive deviations of stablecoins receive greater spillovers from external markets than negative deviations. For example, USDT positive deviations receive more spillovers from DXY

(5.50%) and the S&P 500 (6.54%) compared with their negative counterparts (3.66% and 4.00%, respectively). For both USDC and TUSD, positive deviations receive higher spillovers from all four factors than negative deviations. In the case of USDP, positive deviations receive greater spillovers from Ethereum (5.02%) and the S&P 500 (4.39%). The results further indicate that positive deviations of stablecoins also receive and transmit more spillovers among themselves, suggesting intensified connectedness within the group. Additionally, the 'To others' row shows that positive deviations transmit higher spillovers to others compared with negative deviations.

Table 2.6. The Connectedness between stablecoin positive max deviation and external factors

	USDT	USDC	TUSD	USDP	BTC	ETH	DXY	S&P 500	FROM others
USDT	30.28	15.23	17.89	14.72	4.45	4.84	5.50	6.54	69.18
USDC	15.20	31.05	18.27	16.89	4.80	4.86	4.64	4.30	68.95
TUSD	18.27	17.19	26.57	16.47	5.52	6.01	4.76	5.19	73.43
USDP	17.23	16.92	18.22	28.30	4.72	5.02	4.16	4.39	73.46
BTC	8.75	7.07	10.18	6.54	34.33	24.46	4.10	4.57	65.67
ETH	9.73	7.69	11.26	7.30	22.56	32.07	4.37	5.02	67.93
DXY	7.99	5.79	7.95	5.01	5.01	5.33	49.97	12.96	50.03
S&P 500	8.78	6.78	8.84	6.18	5.13	5.40	11.42	47.48	52.52
TO others	85.58	78.51	93.93	73.10	52.18	55.93	38.95	42.97	521.17
NET spillovers	16.40	9.59	20.50	-0.35	-13.49	-12.00	-11.08	-9.55	TSI = 65.14%

Table 2.6 demonstrates the results of average spillovers among positive stablecoin maximum deviation and factors including volatility of Bitcoin, Ethereum, DXY and S&P 500. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1. The values are percentages. Each column denotes the spillovers that factor in the first row in this column transmits to each variable, each row denotes the spillovers that factor in the first column receives from each variable. The values are the percentage of volatility spillover and the sum of each row is 100. The total spillover index, which appears in the lower right corner of the table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

Table 2.7.The Connectedness between stablecoin negative max deviation and external factors

	USDT	USDC	TUSD	USDP	BTC	ETH	DXY	S&P 500	FROM others
USDT	47.33	13.24	9.82	9.85	6.17	5.94	3.66	4.00	52.67
USDC	19.07	42.20	14.54	12.68	3.24	2.69	2.72	2.87	57.80
TUSD	15.10	14.87	38.51	15.73	4.44	3.92	3.74	3.69	61.49
USDP	15.68	11.78	15.13	39.94	4.87	3.91	5.24	3.45	60.06
BTC	5.78	3.92	3.75	4.56	43.93	31.09	3.73	3.25	56.07
ETH	5.64	2.78	3.04	2.99	31.87	45.95	3.80	3.94	54.05
DXY	9.13	5.83	6.21	8.01	4.18	4.07	50.36	12.21	49.64
S&P 500	9.62	5.87	6.37	5.87	4.01	4.34	9.91	54.00	46.00
TO others	80.02	58.29	58.86	59.69	58.77	55.95	32.80	33.41	437.78
NET spillovers	27.35	0.49	-2.63	-0.37	2.70	1.90	-16.86	-12.59	TSI = 54.72%

Table 2.7 demonstrates the results of average spillovers among negative stablecoins maximum deviation and factors including volatility of Bitcoin, Ethereum, DXY and S&P 500. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a TVP-VAR model of 10-step ahead forecasts. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1. The values are percentages. Each column denotes the spillovers that factor in the first row in this column transmits to each variable, each row denotes the spillovers that factor in the first column receives from each variable. The values are the percentage of volatility spillover and the sum of each row is 100. The total spillover index, which appears in the lower right corner of the table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

The stronger connectedness associated with positive deviations suggest an asymmetric connectedness between stablecoin maximum peg deviations and four external factors we investigate, where positive deviations are more strongly influenced by and connected with these markets. The results contrast with previous empirical research that suggests that negative volatility spillovers tend to exhibit greater connectedness among markets, as negative volatility dominates during periods of crisis and adverse market conditions (Youssef et al., 2021; Ji et al., 2019; Baruník et al., 2017).

We argue that the asymmetric connectedness of stablecoins differs from previous literature because the influence of external markets is more likely to create buying pressure. Specifically, when the price of Bitcoin or other altcoins rises, stablecoins are frequently issued in response to these cryptoasset gains (Kristoufek, 2022). The issuance of stablecoins after gains reflects investors' growing demand for stablecoins to trade and invest in cryptoassets, creating short-term buying pressure, leading to positive price deviations. Conversely, during downturns in cryptocurrency markets, stablecoins are often used to support the prices of non-stable cryptocurrencies (Griffin and Shams, 2020), which is broadly accompanied by a rise in trading volume (Wei, 2018). This also leads to an increasing demand for stablecoins. Furthermore, stablecoins are also considered as a safe haven during periods of heightened market volatility (Baur and Hoang, 2021; Wang et al., 2020), which further increases demand for stablecoins. These growing demands for stablecoins led by external factors, creating additional buying pressure, lead to the stronger connectedness with positive price deviations compared to negative ones.

Overall, we find the heightened volatility in non-stable cryptocurrencies market and traditional financial markets is more likely to linked with positive deviations of stablecoins, causing different asymmetric connectedness in stablecoins markets.

2. 5. 5. Robustness

Our findings show that the spillover index based on the TVP-VAR model in conjunction with the dynamic connectedness approach by Diebold and Yilmaz (2009, 2012, 2014). The time-varying coefficients and error covariances are used to estimate the spillover indices of Diebold and Yilmaz (2009, 2012, 2015). As mentioned above, there are only two input parameters in this TVP-VAR model, the H-step ahead forecast horizon and the lag length p. The H-step forecast horizon is set to 10 days, and the lag length of the TVP-VAR model corresponds to the optimal lag length based on the Bayesian information criterion (BIC), and it is set to one. As a robustness check of the model, we have considered different forecast horizons (namely, $H = 15$, $H = 20$ and $H = 30$ days) with TVP-VAR model. The empirical findings are very similar to those reported in the paper.

Additionally, following Elsayed and Sousa (2024), we also compute volatility spillovers by using Quantile-VAR model (QVAR) to check the robustness of our research. In this framework, the estimated spillover index could overcome the outlier sensitivity problem of VAR model and captures potential asymmetry, as it is calculated based on the conditional median rather than the conditional mean (Elsayed and Sousa, 2024). Our findings show that the total spillover index based on the QVAR model closely matches that estimated from TVP-VAR model. However, there is slightly difference between them, which TVP-VAR is more sensitive to market shocks and adjusts faster than QVAR. The dynamic total connectedness of volatilities is presented in Figure 2.5.

As can be seen in Figure 2.5, similarly, the connectedness among stablecoins and these factors estimated by QVAR model is also strong and largely time-varying. However, compared with Figure 2.2, the QVAR fails to capture certain surges in December 2018, September 2021, and June 2023. This highlights the advantage of the TVP–VAR framework in capturing connectedness fluctuations more effectively, especially during episodes of heightened volatility.

The advantage of TVP-VAR comparing to QVAR has been confirmed in previous empirical research (Korobilis and Yilmaz, 2018; Antonakakis *et al.,* 2020). They show that the connectedness index from the TVP-VAR model captures abrupt turning points better than the one obtained from other rolling-windows VAR estimates. As the TVP-VAR shows more pronounced jumps during important crisis moments, it captures the intensification of tensions in financial markets more accurately and timely than other fixed-coefficients rolling-windows VAR models. We also the compute directional pairwise spillovers between stablecoins and these markets through a QVAR model, which show similar values with TVP-VAR but fails to capture some spikes as well. For brevity, these results are not reported in the paper.

Figure 2.5. Dynamic Total spillover effects generated by QVAR.

Figure 2.5 displays the dynamic total connectedness index between stablecoin and four external factors, including Bitcoin, Ethereum, DXY and S&P 500. It is based on the generalized forecast-error variance decomposition (GFEVD) obtained from the estimation of a Quantile -VAR model of 10-step ahead forecasts, the quantile is set the 20th percentile of both the upper and lower tails to capture extreme values. The sample period is November 1, 2018 – December 31, 2023. The lag length is selected in accordance with the (minimum value of the) Bayesian information criterion (BIC), which is set to 1. The values on vertical axis are percentages.

2. 6. Discussions

Drawing on theories of volatility spillovers and market integration (Liu and Pan, 1997; Bekaert and Harvey, 2003; Beirne et al., 2013), this study investigates the potential drivers of stablecoin volatility. We examine these dynamics primarily through the VAR-based spillover framework proposed by Diebold and Yilmaz (2009, 2012, 2015). The strong total spillover effects indicate that shocks from non-stable cryptocurrencies and traditional assets can be transmitted to stablecoins, suggesting strong financial linkages between stablecoins and their volatility drivers. Our findings show that these external factors representing non-stable cryptocurrencies and traditional assets markets are important drivers of stablecoin volatility, and that their influence is time-varying and heavily dependent on market conditions.

The time-varying spillover effects demonstrate that the market connectedness and integration intensify during volatile episodes. This intensification may be driven by investors seeking safe havens during turbulent periods, often amplified by large-scale monetary interventions (Kumar et al., 2022). These results are consistent with Meteor Showers hypothesis and financial contagion theory (Engle et al., 1988), which suggest that financial distress spreads across regions or markets during crises, thereby increasing integration and spillovers (Engle et al., 1988; Liu and Pan, 1997; Bekaert and Harvey, 2003; Beirne et al., 2013; Hung and Vo, 2021). Our research proves that financial contagion theory is applicable to emerging markets, particularly in cryptocurrencies markets.

Furthermore, our analysis shows that as speculative assets, Bitcoin and Ethereum transmit strong volatility spillovers to stablecoins, which intensify during periods of market stress. We find that stablecoins consistently receive volatility shocks from these leading cryptocurrencies, particularly in times of uncertainty. In contrast, the spillovers from DXY and the S&P 500 are relatively weak under normal conditions, indicating limited market linkage between traditional financial markets and stablecoins. However, during episodes of global uncertainty—such as the Covid-19 crisis—the spillovers from DXY and the S&P 500 to stablecoins become significantly stronger. This demonstrates that shocks from traditional markets can also be transmitted to stablecoins during crises, contradicting earlier claims that stablecoins could act as safe-haven assets against volatility in cryptocurrencies or traditional markets.

In addition, we find evidence of asymmetric connectedness between stablecoin deviations and external factors. Unlike previous studies of traditional financial markets, which typically find stronger linkages for negative returns (Longin and Solnik, 2001; Ang and Chen, 2002; Youssef et al., 2021; Shahzad et al., 2021), our results suggest that positive deviations of stablecoins exhibit higher connectedness with external volatility. This does not necessarily conflict with contagion theory, since market integration is still intensified during volatile periods. However, in the case of stablecoins, extreme conditions in non-stable cryptocurrency markets are more closely associated with positive deviations. This is because external volatility is more likely to drive short-term demand for stablecoins, creating a price premium (Kristoufek, 2021; Griffin and Shams, 2020; Łęt et al., 2023).

Overall, our results fit into the spillover theory(Bekaert and Harvey, 2003; Engle et al., 1990), showing that market integration and volatility transmission between stablecoins and external factors intensify during periods of turbulence. However, the intensified financial linkage and spillover effects between stablecoins and these factors undermines the potential of stablecoins as a safe haven against non-stable cryptocurrencies or traditional assets.

2. 7. Conclusions

This paper provides a comprehensive analysis of the drivers of stablecoin volatility, employing linear regression alongside the spillover approach proposed by Diebold and Yilmaz (2009, 2012, 2015), combined with the TVP–VAR model (Koop and Korobilis, 2014; Antonakakis and Gabauer, 2017). We examines the relationships between volatility of stablecoin and that of five external markets that could potentially impact stablecoins volatility, including Bitcoin, Ethereum, DXY, S&P 500 and gas price of Ethereum blockchain.

Our results indicate that Bitcoin and Ethereum exert a strong influence on stablecoin volatility across the entire sample period, while DXY and the S&P 500 significantly affect stablecoins during periods of heightened volatility. We further find that volatility spillovers from these markets to stablecoins intensify notably under turbulent market conditions. These results remain robust across different model specifications and parameter choices. Moreover, by distinguishing between positive and negative price deviations, our study uncovers asymmetric spillovers: positive deviations display stronger spillover effects than negative deviations. This suggests that volatility spillover and market integration theories are applicable to stablecoin markets (Liu and Pan, 1997; Bekaert and Harvey, 2003; Beirne et al., 2013).

To the best of our knowledge, this is the first empirical study to investigate the relationship between stablecoin volatility and both U.S Dollar index and the S&P 500 index. we extend prior research (Hoang and Baur, 2021; Lyons and Viswanath-Natraj, 2023; Bullmann et al., 2019) by identifying additional drivers of volatility in fully-backed stablecoins. We push beyond past work that primarily focuses on the relationship between stablecoins and major cryptocurrencies, to the relationship with currency market and equity market. Methodologically, we also extend the spillover effects framework of Diebold and Yilmaz (2009, 2012, 2015) to capture directional pairwise spillovers, thereby offering more granular insights into the volatility transmission from external drivers to stablecoins.

Our results are based on daily data for four leading fully-backed stablecoins over 2018 — 2023. The data employed offers many benefits for the exploration of drivers of stablecoin volatility. First, this five-year horizon is substantial for such a relatively young market (Łęt et al., 2023), capturing key events in the evolution of stablecoins. In addition, the data of stablecoins price is drawn from the CoinMarketCap, which is calculated by averaging the prices from a bunch of centralized exchanges and weighted by volume. This strengthens our confidence in the robustness of our conclusions, as it avoids potential price bias from selecting individual exchanges. Nevertheless, the reliance on daily data may overlook faster-moving dynamics, since certain deviations are resolved within a single day (Lyons and Viswanath-Natraj, 2023). Future research could therefore employ intraday data to capture short-lived price dynamics more precisely. A further limitation is that our study considers only a restricted set of external factors, potentially omitting other influences on stablecoin volatility.

The cryptocurrency market, particularly stablecoin market, remains an emerging and rapidly evolving space, characterized by frequent changes and limited regulatory oversight.[9] As the cryptocurrency market is developing quickly, the transmission mechanism of volatility and market connectedness might change, but more generally, our result may apply to other new asset that may come into emerging in the future. Studying cryptocurrencies and stablecoins therefore offers valuable insights into how assets interact in new and evolving financial markets.

[9] https://home.treasury.gov/news/press-releases/jy0454

Chapter 3

Stablecoin Mispricing: Cross-Exchanges Arbitrage

Chapter 3

Stablecoin Mispricing: Cross-Exchanges Arbitrage

Abstract

This paper analyzes cross-exchanges mispricings of stablecoins where arbitrage is allowed. By utilizing high-frequency quotes and trades data of two leading fully-backed stablecoins on three large centralized cryptocurrency exchanges, we find that cross-exchanges mispricings that allow arbitrage are prevalent. Analysis on duration and profitability of these mispricings indicate they are exploitable and profitable after considering transaction cost. Sensitivity analysis confirms that mispricings are profitable at different levels of transaction cost. Additionally, we find market is more active and facing more one-sided order imbalance on days with arbitrage opportunities. Further intraday market characteristics analysis unveils that market microstructure factors and asynchronous price adjustments between exchanges both contribute to the mispricings.

Key words : Arbitrage, Mispricing, Stablecoin, Market Microstructure

3.1. Introduction

Since its inception in 2009 as an open-source digital currency, cryptocurrency has attracted growing attention of researchers, policy-makers, and traders. Among all cryptocurrencies, Bitcoin has has received particularly widespread coverage the financial media, largely due to its phenomenal surge in transaction volume and market cap. However, due to the high volatility (Yermack, 2015), many argue that Bitcoin could not be characterized as a ‘fiat money’ (Selgin 2015). This has motivated the development of stablecoins, which potentially aim to offer a less volatile alternative.

Stablecoin represents a novel form of cryptocurrency that holds the potential to establish a decentralized financial system that is free from traditional financial intermediates. Their primary objective is to enable universally accessible monetary transactions and payments without relying on trusted third parties. Stablecoins are generally less volatile than traditional cryptocurrencies as they are backed by collateralized pegs and designed to maintain a fixed value. The role of stablecoins has risen dramatically since 2019, with estimates of total trading volume of Tether (USDT), the largest stablecoin in supply, reaching twice the trading volume of Bitcoin by the first quarter of 2024.

Stablecoins broadly serve as the initial gateway for cryptocurrency investors venturing into the market (Mita et al, 2019; Moin et al, 2020). Moreover, they play a central role in the digital-asset economy, as a medium of exchange (Yermack, 2015), a stabilizing force for the prices of other cryptocurrencies (Griffin and Shams, 2020), and a safe haven for investors during high volatile period (Baur and Hoang, 2021; Feng et al., 2024). Their relatively stable value also makes them a more reliable means of preserve value over time (Kristoufek, 2021).

However, as stablecoin gain prominence, recent years have seen an increasing amount of evidence suggesting stablecoins exhibit unexpected excess volatility and mispricings (Hoang and Baur, 2021; Grobys et al., 2021). Also, the causes of stablecoin depeggings and mispricings have gained attention in prior literature, which are attributed to external and internal reasons. Some researchers attribute mispricings to the strong correlation between stablecoins with volatile cryptocurrencies like Bitcoin (see. Duan and Urquhart, 2023; Hoang and Baur, 2021; Grobys et al., 2021). Others focus on internal factors, where they find mispricings are influenced by design mechanism and range of issuance. Jarno and

Kołodziejczyk (2021) find that fully-backed stablecoins experience fewer mispricings compared to those with more complex structures. Similarly, Kozhan and Viswanath-Natraj (2021) show that more stable collateral contributes to greater price stability. Lyons and Viswanath-Natraj (2023) further demonstrate that decentralized issuance of stablecoins leads to narrowed price deviations.

These mispricings and depeggings of stablecoins attracts intensive arbitrage activities between primary and secondary markets, which could in turn help to remove these mispricings and stabilize stablecoins' price. Pernice (2021) shows that arbitrage activities between primary and secondary markets can enhance the stability of theoretical models of stablecoins. Lyons and Viswanath-Natraj (2023) offer a day-to-day arbitrage analysis and demonstrate that increased arbitrage activity of stablecoins between primary and secondary markets reduces the price deviations from their pegs.

These arbitrage activities are widespread in stablecoin markets as investors have faith in stablecoins when their prices are in discount due to the pegging and fully reserve mechanism (Lyons and Viswanath-Natraj, 2023). The issuers of stablecoins claimed that they will always issue or redeem stablecoins at pegged price. This promise encourages traders to purchase discounted stablecoins, with the expectation that such price deviations are typically short-lived and offer near risk-free profits once prices converge back to the peg. Moreover, because stablecoins are explicitly designed to maintain price stability, the usual risks associated with arbitrage in other crypto-assets such as inventory risk are substantially reduced.

Taken together, prior literature has evolved from viewing stablecoins as a medium of exchanges and potential safe haven assets to increasingly research their mispricings. More recent studies have focused on the arbitrage *between* primary and secondary markets induced by mispricings. However, existing literature largely overlooks mispricings and arbitrage opportunities *within* secondary market. In particular, cross-exchanges mispricings of stablecoins have received limited attention. This area is especially relevant as secondary market typically involves lower capital thresholds and transaction costs, making it more accessible for arbitrage activity than can help correct subtle de-pegging deviations and improve the price stability of stablecoins.

To address this research gap, our study aims to answer two research questions (i) Do mispricings of stablecoins exist across cryptocurrency exchanges that enable arbitrage? (ii) What factors contribute to the occurrence and potential profitability of these arbitrage opportunities? Answering these questions is important for assessing and improving the stability of stablecoins, which function as the medium of exchange and storage of value in the broader cryptocurrency markets (Baur and Hoang, 2021; Kristoufek, 2021).

To address these research questions, we analyse the mispricing and arbitrage activity for USDT and USDC—the two largest USD-pegged stablecoins by market capitalization—across three leading centralized cryptocurrency exchanges: Kraken, Bitstamp, and BinanceUS. We collect millisecond-level, tick-by-tick trade and order book data of USDT/USD and USDC/USD trading pairs from these three exchanges, spanning from January 1st 2022 to June 30th 2023.

We investigate the mispricings of these two stablecoins across exchanges which could create arbitrage opportunities, and calculate the associated profits and durations and to see how much meaningful profits they could yield? Subsequently, following the approach proposed by Marshall et al. (2013), we examine how minute-level changes in market microstructure factors, including order imbalance, bid-ask spreads, market depth and return standard deviation, during periods of mispricing are associated with the occurrence of arbitrage opportunities. We choose bid-ask spread, market depth, order imbalance and return standard deviation to represent market microstructure, as market liquidity and order flow are the key factors that could reflect the information asymmetry and prevailing trading conditions (Kyle, 1985; Hasbrouck, 1991; Chordia and Swaminathan, 2000).

Finally, we assess the speed of price discovery across exchanges by applying impulse response functions, to examine whether difference in the speed of price adjustments of exchanges contribute to stablecoin mispricings.

Our study yields several important findings. First, we find that mispricings of stablecoin largely exist between exchanges and remain profitably exploitable even when transaction costs are considered. The average duration of these mispricings is under five minutes, with over 75% lasting less than three minutes. Compared to earlier studies reporting longer-duration mispricings in the cryptocurrency market (Makarov and Schoar, 2020; Crépellière et al., 2023), these quickly corrected mispricings implies active participation by arbitrageurs in stablecoin market, indicating that even small price deviations are seen as worthwhile trading opportunities. More importantly, these quickly removed arbitrage opportunities suggest the market efficiency of stablecoins is dynamic over time, which supports the Adaptive Market Hypothesis, where inefficiencies are not permanent and they are corrected as investors learn and adapt (Lo, 2004).

Second, our analysis reveals market microstructure factors drive stablecoins mispricings. In particular, we observe that arbitrage opportunities are more likely to arise on days when market is active and facing one-sided order flow, and the profitability of mispricings tends to be higher as well when market is in such scenario. Additionally, our intraday market microstructure analysis suggests liquidity, trading volume and return standard deviation contribute to the arise of arbitrage opportunities. Specifically, we show bid-ask spreads increase and market depths decrease minutes before, during and after mispricings, which is indicative of a decline in liquidity. Also, trading volume and the standard deviation of trade-to-trade returns increase sharply prior to the occurrence of arbitrage opportunities. The changes of order imbalance indicates overpriced (underpriced) stablecoins tend to face selling (buying) pressure during arbitrage opportunity, suggesting investors who seek to exploit cross-exchanges arbitrage are actively doing so.

Lastly, our results suggest that differences in price discovery contribute to the mispricings in stablecoin markets. The results of impulse response function analysis shows that these exchanges have different response speed to market shocks, indicating the asynchronous price adjustments to information between exchanges also drives mispricings.

Arbitrage is not always risk-free or costless in practical market (Shleifer and Vishny, 1997; Mitchell et al., 2002), limits and risks which may hinder arbitrageurs from fully exploiting stablecoin mispricings across exchanges include trading fees, mispricing durations, information acquisition costs, convergence risk, and inventory risk (Marshall et al., 2013). Nevertheless, in our case, we argue that these risks and costs are not substantial enough to prevent the exploitation of the identified arbitrage opportunities. First, our empirical analysis demonstrates that the potential profits from arbitrage can exceed the trading fees imposed by the exchanges, and the durations of these mispricings are long enough to allow arbitrageurs to identify and act upon them. Second, many crypto exchanges and database provide free and real-time API access to order book data, making information acquisition relatively low-cost and easily accessible. Lastly, due to the full reserve backing and redemption mechanisms of the stablecoins in question, significant and persistent price deviations from their pegs are rare. This reduces inventory risk as the likelihood of unfavorable price movements during inventory holding is minimal. Also, we track identical assets in different exchanges, which avoid the convergence risk.

Our contribution is multifold. To the best of our knowledge, this is the first empirical study that analyzes the cross-exchanges mispricing and arbitrage of stablecoins. Our research uncovers a previously under explored arbitrage mechanism in the stablecoins market that might help to further reducing the size of peg deviations. As a further contribution, we shed new light on the drivers of stablecoins mispricings. Our research suggests market microstructure factors as well as different price discovery speed between exchanges contribute to the arise of mispricings. Moreover, we provide empirical evidence supporting the Adaptive Market Hypothesis, as the frequent occurrence and rapid correction of mispricings suggest that stablecoin market efficiency evolves over time in response to changing market conditions and arbitrageur behavior.

The remainder of the paper is structured as follows. Section 3.2 reviews related literature and Section 3.3 describes sampled datasets used in the analysis. In section 3.4, we illustrate our methodology and models. In Section 3.5 we present empirical results and sensitivity analysis. Section 3.6 is discussions and Section 3.7 is conclusions.

3. 2. Related literature

3. 2. 1. Volatility of stablecoin

The creation of stablecoin attract researchers' attention as it potentially solves the problem of huge volatility for cryptocurrency to be a medium of exchange (Yermack, 2015). Stablecoins are pegged to different assets such as fiat and gold (Mita et al, 2019 ; Moin et al, 2020), and the pegging mechanism of stablecoins makes them more similar to major fiat currencies than to speculative assets (BIS, 2019; IMF, 2019). The stability of stablecoin arouses interest of many researchers as it claims to be completely stable. However, in reality, stablecoins are proved not absolute stable, at least are less stable than fiat, despite they are more stable than equity assets and traditional non-stable cryptocurrencies (Hoang and Baur, 2021; Grobys et al., 2021).

This excess volatility of stablecoin, which is unexpected, attracts the interests of researchers, they are trying to explain this excess volatility of stablecoin from two perspectives. The first one is design mechanism, previous research found that algorithm stablecoins are more volatile than fully-backed ones due to the lack of investors' confidence and arbitrage channels when algorithm stablecoin is priced at a discount (Jarno and Kołodziejczyk, 2021; d'Avernas et al. 2022; Gadzinski et al., 2023; Kozhan and Viswanath-Natraj, 2021; Lyons and Viswanath-Natraj, 2023). The second reason of stablecoin excess volatility is the correlation between stablecoins and non-stable cryptocurrencies such as Bitcoin. In previous literature, stablecoin is found to be linked with volatile non-stable cryptocurrencies in trading volume (Hoang and Baur, 2021) and price volatility (Grobys et al., 2021, Kristoufek, 2021;). Also, stablecoins are primarily used to trade Bitcoin and could support Bitcoin price during market downturns (Hoang and Baur, 2021; Kristoufek, 2021; Griffin and Shams, 2020), making stablecoins strongly correlated with tradings of non-stable cryptocurrencies. The imperfect algorithm design and strong correlations between stablecoin and volatile traditional cryptocurrency bring unexpected volatility to stablecoin. Very limited research investigate the impacts of traditional markets on stablecoins volatility, focusing on interbank rate (Nguyen et al., 2022).

After determining this excess volatility of stablecoin and its potential drivers, researchers turn to seek ways to reduce the volatility of stablecoin. The arbitrage activity between primary and secondary market has been shown to play a key role in maintaining stablecoin stability and removing the price de-pegging. Pernice (2021) find theoretic stablecoin models might benefit from arbitrage between primary and secondary market. Lyons and Viswanath-Natraj (2023) show that decentralized issuance of stablecoin reduce the size of peg deviations due to more arbitrage activities between primary and secondary market.

We view our paper as complementary to this literature. To the best of our knowledge, the research on stablecoin mispricing and arbitrage focus mainly on between primary and secondary market, potentially overlooking the arbitrage within secondary market, which raises an interesting research gap that more arbitrage route is needed to remove the subtler mispricings of stablecoin. We contribute to this literature by providing a new possible route of arbitrage in stablecoin market. In particular, we push beyond past work focusing on stablecoin arbitrage only between primary and secondary market, to cross-exchanges arbitrage.

3. 2. 2. Arbitrage

3. 2. 2. 1. Definition of arbitrage

Arbitrage is defined as the trading activity of exploiting of price differences between markets or instruments to generate a risk-free profit. The concept rests on the fundamental financial principle that identical or similar assets should not trade at different prices in efficient markets. The definition of arbitrage is much shaped by the Law of One Price (LOOP) and Efficient Market Hypothesis (EMH). Law of One Price (Samuelson, 1965) asserts that in the absence of transaction costs, identical goods should have the same price across different markets. Fama (1970) integrates the concept of arbitrage into his Efficient Market Hypothesis (EMH), arguing that arbitrageurs are key players who exploit and thereby eliminate inefficiencies in markets, ensuring that prices reflect all available information. Additionally, under the Adaptive Market Hypothesis proposed by Lo (2004), arbitrage is not a guaranteed risk-free activity as assumed in classical theory, and it is not a static, risk-free mechanism but a dynamic process shaped by the adaptive behavior of market participants and evolving market conditions.

3. 2. 2. 2. Arbitrage theoretical foundation

The term arbitrage first appeared in the early 19th century (Haupt, 1870), and the theoretical foundation of arbitrage was expanded significantly in 20th century. Ross (1976) proposed the Arbitrage Pricing Theory (APT), which claims that asset prices are driven by multiple systematic factors rather than a single market portfolio, as suggested by the Capital Asset Pricing Model (CAPM). APT theory is grounded in the principle of arbitrage, which suggests that asset is arbitrage-free priced and portfolios with identical risks cannot have different expected returns. APT claims that asset prices could adjust and no arbitrage opportunities exist, aligning with the Law of One Price.

Under Efficient Market Hypothesis (EMH) proposed by Fama (1970), arbitrage opportunities are rare and not persistent in efficient markets, because competition among arbitrageurs ensures that prices reflect all available information almost instantaneously (Fama, 1970). One of the most important implications of EMH is no free lunch, which means arbitrageurs in efficient markets can only earn normal profits commensurate with their level of risk, not risk-free profits. This implication is pretty much based on the prerequisite that investors act rationally or that irrational actions are quickly offset by arbitrageurs. However, this prerequisite has been criticized that irrational behaviors and cognitive biases may persist, these irrational trading can create and sustain mispricings (Shleifer and Vishny, 1997).

Then Lo (2004) proposed Adaptive Market Hypothesis (AMH), reinterprets traditional market efficiency theories within the framework of evolutionary principles, including implications about arbitrage. According to AMH, markets are not always efficient and market condition is dynamic. Arbitrage opportunities could exist and persist because market participants adjust to the changing conditions at different speed, and mispricings can occur due to the differences in price discovery times (Marshall et al., 2013). Additionally, the effectiveness of arbitrage strategies depends on the state of market efficiency, which evolves over time. During crises, inefficiencies are more prevalent, and thus arbitrage opportunities become more frequent and persist longer, reflecting the adaptive nature of markets as described by AMH (Cont, 2001; Kim and Shamsuddin, 2008). Our paper contribute to this strand of literature by examining these implications of AMH on arbitrage in stablecoin markets.

3. 2. 2. 3. Theory of limits of arbitrage

AMH theory (Lo, 2004) implies that the evolutionary processes of market could lead to arbitrage opportunities, which requires no capital and entails no risk in theory. However, in reality, almost all arbitrage requires capital, and is typically risky (Shleifer and Vishny, 1997; Mitchell et al., 2002). In practical trading, there are limits and risks that prevent arbitrageurs from executing arbitrage trading to eliminate mispricings.

Fundamental risk is one of the major risk that limits arbitrageur to trade (Shleifer and Vishny, 1997; Mitchell et al., 2002), which refers that mispricings may take time to correct, and the arbitrageur bears the risk that prices may move further away from there fundamental values during that time. This risk usually exists when arbitrageur doing arbitrage between two different assets, such as between S&P 500 and associated ETF. The potential anomalies in financial markets prevents arbitrageurs from eliminating mispricings. De Long et al. (1990) owe this further divergent from fundamental values to irrational noise traders. Mitchell et al., (2002) investigate the arbitrage opportunities in equity market, they find imperfect information also limits the arbitrage trading to remove the price deviations from fundamental values. Moreover, inventory risk usually comes with fundamental risk as arbitrageurs might facing high cost of capital. Inventory risk refers to the potential loss that arises when they must hold positions in mispriced asset while waiting for prices to converge, and during this period, the asset's price may move unfavorably. Shleifer and Vishny (1997) point out the fundamental risks and inventory risk, highlighting the possibility that prices might diverge even further, where arbitrageurs have to be liquidated due to margin calls before the final convergence occurs.

Additionally, arbitrageurs are broadly facing a series of costs and limits to execute arbitrage tradings. Gromb and Vayanos (2010) conduct a comprehensive survey of the theoretical models, they find arbitrageurs are facing a series of limits to arbitrage besides fundamental risks, including short-selling costs, leverage and margin constraints, and constraints on equity capital. Also, information costs are also another limits to arbitrage. Grossman and Stiglitz (1976, 1980) suggest that obtaining information is a costly process. In high frequency trading (HFT) period, useful information for arbitrage might expire in seconds (Alsayed and McGroarty, 2014; Marshall et al., 2013; Lyons and Viswanath-Natraj, 2023). Then the profitability of arbitrageurs needs to cover the high cost of acquiring fast information (Marshall et al., 2013), which is a significant limit to arbitrage.

In cryptocurrency markets, several limits to arbitrage have been identified, including trading speed, short-selling constraints, technical infrastructure and capital control (Fischer et al., 2019; Makarov and Schoar, 2020). Our paper contribute to this strand of literature by investigating potential profitability of arbitrage opportunities in stablecoin markets after considering limits to arbitrage, including transaction costs, responding speed of arbitrageurs and short-selling constraints.

3. 2. 2. 4. Empirical review of mispricing and arbitrage

Our paper also contribute to the literature that focus on the empirical side of mispricings and arbitrage. In real-world markets, empirical evidence confirms that prices can deviate from the Law of One Price, even in the presence of arbitrageurs. (e.g., De Long et al., 1990; Gromb and Vayanos, 2002; Gromb and Vayanos, 2018), arbitrage profits could be made due to those mispricing (e.g. Froot and Dabora, 1999; Mitchell et al., 2002; Gagnon et al., 2010; Alsayed and McGroarty, 2012). Price deviation and arbitrage opportunities are observed in different markets, including ETF market (Engle and Sarkar, 2006; Ackert and Tian, 2000; Richie et al., 2008; Marshall et al., 2013;), stock market (Rosenthal and Young, 1990; Froot and Dabora, 1999; Mitchell et al., 2002; Schultz and Shive, 2010) and cryptocurrency market (Kroeger and Sarkar, 2017; Pieters and Vivanco, 2017; Makarov and Schoar, 2020; Borri and Shakhnov, 2022;).

In these markets, mispricings are found to exist and persist for a long time. Froot and Dabora (1999) show mispricing in stocks listed in different locations can prevail for over 4 years. Mitchell et al. (2002) show divergence in the price of a parent company and listed subsidiary can last for over 5 months, Schultz and Shive (2010) show mispricing in a class of stock with different voting rights can persist for 2 years. The price deviation of non-stable cryptocurrencies such as Bitcoin, could persist for years as well (Makarov and Schoar, 2020; Crépellière et al., 2023). The price deviation of stablecoin between primary market and secondary market could lasts for over 10 days (Lyons and Viswanath-Natraj, 2023).

On the contrary, our results are closer to the cases that mispricings are very quickly removed. Alsayed and McGroarty (2012) find stock-ADR mispricing reduces by half in around 7 min, Busse and Green (2002) who show prices converge to efficient levels following CNBC reports in 1–15 min depending on whether the report is good or bad news. Moreover, Chordia et al. (2005) find investors take between 5 and 60 min to restore prices to efficient levels following order imbalances. Marshall et al. (2013) shows mispricings between ETFs are removed in a few minutes. The cross-exchanges mispricings and their average duration are overlooked in previous literature, we extend this literature stream by filling this research gap.

3. 2. 3. Market microstructure and arbitrage of stablecoin

Market microstructure theory has evolved as a distinct field in financial economics, focusing on the mechanisms of trading under market structures. Its development reflects the interplay between theoretical innovation and empirical testing, driven by the need to understand how market design, information, and trading strategies influence price formation, liquidity, and market efficiency.

3. 2. 3. 1. Market microstructure theoretical foundation

The early theoretical foundation of market microstructure highlight the role of adverse selection and asymmetric information in trading. Akerlof (1970) proposed "Market for Lemons"[10] theory, claiming asymmetric information could lead to adverse selection. Then Garman (1976) and Ho and Stoll (1981) introduced and expanded the inventory theory of market making, pointing out market maker adjust bid-ask spread by considering not only the inventory cost, but also the adverse selection risks. Then, Kyle (1985) proposed a market model with three kinds of traders, which described how informed traders exploit private information, and influence prices through order flow. Glosten and Milgrom (1985) showed traders with superior information leads to a positive bid-ask spread, and market makers adjust bid-ask spreads to protect against informed traders, highlighting the role of adverse selection in price formation. Amihud and Mendelson (1986) regarded liquidity as a factor in asset returns, showing that assets with higher bid-ask spreads should yield higher expected returns. Stoll (1989) decomposed bid-ask spreads into several components, which attribute to inventory holding costs, adverse selection, and order processing, respectively. Hendershott et al. (2011) shows that algorithmic trading reduces bid-ask spreads by decreasing information asymmetry, suggesting that high-frequency trading improves market efficiency.

Based on the strong relationship between bid-ask spreads and information asymmetry, market liquidity starts to come into the sight of researchers. Amihud (2002) have expanded liquidity measures to include market depth and price impact. Hasbrouck (1995) synthesized earlier models and provided a framework to understand market design, emphasizing the role

[10] https://en.wikipedia.org/wiki/The_Market_for_Lemons

of trading systems and rules in shaping liquidity and efficiency. Furthermore, not just liquidity, more factors such as trading volume and order imbalance are included in the range of market microstructure. Karpoff (1987) and Lee & Swaminathan (2000) investigate the impact of trading volume on price change and momentum. Madhavan et al. (1997) revealed that order imbalance have significant price impact, highlighting the role of order flow in price discovery.

Market microstructure is also closely correlated with market efficiency and mispricing. In previous literature, market microstructure is broadly considered as a driver of market efficiency, it could affect market efficiency in different ways, including price discovery (Kyle, 1985; Hasbrouck, 1991;), market liquidity (Amihud and Mendelson, 1986;) and information efficiency (Madhavan et al., 1997; Admati and Pfleiderer, 1988). In addition, noise trading can reduce market efficiency by introducing temporary price distortions (Black, 1986; De Long et al., 1990). These market inefficiency caused by market microstructure factors could further lead to temporary mispricings allowing arbitrage (e.g. Grossman and Stiglitz, 1980; Black, 1986; De Long et al., 1990; Amihud and Mendelson, 1986). We contribute to this strand of literature by investigating how stablecoin market microstructure affect its market efficiency, represented by occurrence of mispricings.

3. 2. 3. 2. Empirical review on market microstructure and arbitrage

These above theoretical works have shaped the field of market microstructure, providing tools to analyze diverse markets, including equities, derivatives, and cryptocurrencies in empirical studies. This evolution also reflects an ongoing of empirical application. Overall, the theory of market microstructure has evolved from foundational models of information asymmetry and bid-ask spreads to include complex dynamics in modern markets, such as the mechanism design of trading venue (Madhavan, 2000; Hasbrouck, 1995), market depth (Amihud and Mendelson, 1986; Kyle,1985; Amihud, 2002), order flow and trade informativeness (Hasbrouck, 1991; Easley and O'hara, 1987).

In empirical side, a large body of literature focuses on the relationship between arbitrage and microstructure factors. Coughenour and Shastri (1999) provide a detailed summary that empirical studies of microstructure are mainly in four areas: the bid-ask spread, order flow properties, the Nasdaq controversy, and linkages between option and stock markets. Our research is linked to research on the relationship between arbitrage and bid-ask spread (liquidity) as well as order flow. Arbitrage might impair the market liquidity. Foucault et al. (2017) provide theoretical and empirical evidence that liquidity would decrease when arbitrage opportunities due to lagged adjusts to new information occur. However, arbitrage could also prompt the market liquidity. Kettler et al. (2014) explain arbitrage helps to narrow the bid-ask spread. Gromb and Vayanos (2010) also state that arbitrageurs could provide liquidity when opportunities are due to transient demand or supply shocks. Also, liquidity shocks could facilitates arbitrage opportunities (Ben-David et al., 2018; Roll et al., 2007).

Additionally, the order flow could impact the mispricings and arbitrage opportunities as well. Bossaerts et al. (2018) found the order flow from noise traders could lead to prolonged mispricings. Makarov and Schoar (2020) study the Bitcoin order book snapshots from 34 exchanges, they find the idiosyncratic part of order flow helps explain price deviation between exchanges. Our research contributes to this strand of literature by showing the correlation between market microstructures and stablecoin mispricings. Also, we show that cross-exchanges arbitrage activities of stablecoins are likely to impair the market liquidity.

In cryptocurrency markets, there is also an emerging body of research on the mispricing and microstructure. Mispricing and arbitrage opportunity are frequently observed in cryptocurrency and even stablecoin markets. Mispricings are widespread across exchanges and countries (Kroeger and Sarkar, 2017; Pieters and Vivanco, 2017; Makarov and Schoar, 2020; Borri and Shakhnov, 2022; Jin, 2021; Pernice, 2021; Lyons and Viswanath-Natraj, 2023). In terms of market microstructure, order book dataset enables researchers to analyze various intraday market microstructure factors. Limited studies have focused on the impact of order informativeness (Ghysels and Nguyen, 2019; Makarov and Schoar, 2020), liquidity (Brauneis et al., 2019; Dimpfl, 2017; Dyhrberg et al., 2018; Koutmos, 2018), and transaction fees (Easley et al., 2019) on cryptocurrency trading and price deviation. The design mechanism of cryptocurrency and capital control could also lead to the price deviation. (Lyons and Viswanath-Natraj, 2023; Pernice, 2021; Makarov and Schoar, 2020). We extend this existing body of work by identifying different speed of price discovery between exchanges lead to stablecoin mispricings, creating arbitrage opportunities.

3. 3. Data

We focus on USDT/USD and USDC/USD pairs in three leading cryptocurrency exchanges that provide both USDT/USD and USDC/USD trading pairs, Kraken, Bitstamp and BinanceUS. USDT and USDC are the two largest stablecoins, which account for over 90% market cap and over 80% trading volume among all stablecoins (June 2024). We collect high frequency tick-by-tick snapshot of limit order data and trade data from CryptoTick.com. CryptoTick is a database that offers high frequency historical trade and limit order data from a bunch of centralized crypto exchanges, and it is the only database we find that provide pay as you go model to buy dataset we need without subscribe.

Snapshot of limit order data describes the status of the top of the limit order book and is updated whenever there is a change. This data includes the best bid and ask prices along with the cumulative size of orders resting on the best prices, and it records the order ID, timestamp, best ask price, amount resting on the best ask price, best bid price, and amount resting on the best bid price. Trade data, on the other hand, represents matches between passive and active market participants. Each trade record includes an ID, timestamp, price, size, and the aggressor of the trade (if available). Our dataset spans from January 1, 2022, to June 30, 2023, which includes three major events, crash of Terra, failure of FTX and bankruptcy of Silicon Valley Bank (SVB). We believe the sample period is sufficient for our study, given that the dataset includes over 100 million snapshot of best bid and ask records and more than 40 million trade records. This sample period, which covers the entirety of 2022 and first half of 2023, allows us to observe how major market shocks, such as the Terra crash and the FTX collapse, affected cross-exchange mispricings in the stablecoin market

To begin with, we conduct descriptive statistical analysis on dataset. Descriptive statistics of USDT/USD and USDC/USD quotes data are presented in Table 3.1. From table 3.1, it is clear that the number of updates on best limit order are tremendous, and all of them are over 1 million times in total during sample period. Bitstamp has lowest liquidity for both USDT and USDC as it has widest bid-ask spread and lowest market depth (amount resting on best bid and ask price) while Kraken has the most market depth for both USDT and USDC. Table 3.2 presents descriptive statistics of trades dataset. As can be seen in table 3.2, in each exchange, transactions of USDT are more than that of USDC, and the number of transactions in Bitstamp is less than Kraken and BinanceUS. Additionally, the average trade prices of two stablecoins are pretty close to 1 USD. The average trading size of USDT and USDC are over 1000 USD in three exchanges, and average trading size of BinanceUS is slightly less than that of other two exchanges.

Table 3.1. Summary statistics of snapshot of limit order book data.

	Obs	Average best ask price	Average best bid price	Average amount on best ask	Average amount on best bid
Kraken USDT	25,897,803	1.00026	1.00016	3,354,263	3,618,659
Kraken USDC	6,671,019	1.00004	0.99992	2,693,622	2,179,046
Bitstamp USDT	20,437,476	1.00047	1.00006	14,786	16,827
Bitstamp USDC	32,436,920	1.00010	0.99974	40,634	10,647
BinanceUS USDT	18,747,582	0.99833	0.99821	637,706	1,111,454
BinanceUS USDC	1,961,604	0.99998	0.99987	376,708	373,385

Table 3.1 presents the summary statistics of USDT/USD and USDC/USD snapshot of limit order book data of Kraken, Bitstamp and BinanceUS, collected from Cryptotick. Snapshot of limit order book data describe status of top of the order book, and it will be updated when the status changes. Unit of price and average amount on best ask and best bid is in US dollar. Observation is the number of times that top of the order book has been updated. Sample period is from January 1st 2022 to June 30th 2023.

Table 3.2. Summary statistics of trade data.

	Number of trades	Average trade price	Average trade amount
Kraken USDT	18,600,842	0.99997	4658
Kraken USDC	2,933,822	0.99998	3906
Bitstamp USDT	474,660	0.99889	1786
Bitstamp USDC	233,025	0.99999	3140
BinanceUS USDT	20,190,874	0.99801	1081
BinanceUS USDC	4,907,902	0.99990	1364

Table 3.2 presents the summary statistics of USDT/USD, USDC/USD trades data in Kraken, Bitstamp and BinanceUS, collected from Cryptotick. Trade price and trade amount are both in US dollar. Sample period is from January 1st 2022 to June 30th 2023.

From January 1, 2022, to June 30, 2023, the stablecoin markets experienced several significant disruptions triggered by major events in the broader crypto and financial ecosystem. Three prominent incidents during this period—the failure of Terra in May 2022, the collapse of FTX in November 2022, and the bankruptcy of Silicon Valley Bank (SVB) in March 2023—corresponded with heightened volatility in the prices of major stablecoins, particularly USDT and USDC.

The first crisis, in May 2022, followed the collapse of Terra's algorithmic stablecoin, UST, which shook the market confidence in the broader stablecoins ecosystem. In the aftermath, USDT experienced noticeable price declines across multiple exchanges, with prices briefly falling as low as $0.93 before gradually recovering. This period was characterized by sustained deviations from the $1 peg, particularly for USDT, while USDC demonstrated greater resilience, experiencing only a minor and short-lived drop.

The market shock occurred in November 2022, following the unexpected collapse of FTX, one of the largest cryptocurrency exchanges at the time. Both USDT and USDC again exhibited increased price volatility, although the magnitude of the depegging was smaller compared to the Terra event. USDT remained above $0.97, and most price dislocations were short-lived, with stability returning within two weeks.

The third event took place in March 2023, when Silicon Valley Bank, one of the key custodians of USDC reserves, announced bankrupt. At the time, approximately 8% of USDC's reserves were held at SVB. This event led to a sharp and immediate reaction in the market, with USDC briefly depegging and dropping significantly to 0.7 USD. However, once the U.S regulators confirmed that all deposits at SVB would be protected, the price of USDC quickly rebounded and re-established its peg. Notably, USDC showed stronger resilience in the first two crises but was more directly impacted by the traditional financial sector shock in early 2023 due to its reserve exposure.

Taken together, these episodes illustrate that although stablecoins are designed to maintain price stability through pegging system, they remain vulnerable to systemic events and confidence shocks.

3. 4. Methodology

3. 4. 1. Arbitrage identification

In cryptocurrency market, one cryptocurrency is usually traded on several different exchanges, and thus arbitrage by taking advantage of price deviation cross-exchanges is plausible (Makarov and Schoar, 2020). Cross-exchange arbitrage is naturally suitable for cryptocurrency market, which is based on Law of One Price (Alsayed and McGroarty, 2012; Borri and Shakhnov, 2022). As a lucrative arbitrage trading strategy, cross-exchange arbitrage has been widely used. (Gatev et al., 2006; Chiu and Wong, 2018; Sarmento and Horta, 2020). The basic logic behind cross-exchange arbitrage is quite intuitive. First, identify the investment assets with similar historical price trends to match. Usually, these assets broadly share common components or exhibit a substitute relationship in economic terms, such as ETFs tracing same stocks. When a temporary divergence in their prices occurs, an arbitrage portfolio can be constructed by buying the undervalued asset and selling the overvalued one. When the price divergence cycle ends and the market returns to rationality, the paired assets will typically show a convergence trend, to make the arbitrage portfolio become profitable (Jacobs and Weber, 2015). In our case, cross-exchange arbitrage is quite simple, we track identical stablecoins in several different crypto exchanges, if the bid price of one exchange is higher than the ask price of another, then there exists an arbitrage opportunity that investors could buy at a lower ask price and sell at a higher bid price.

However, several arbitrage constraints exist. First is the transaction cost of arbitrage trading. Cryptocurrency traders on centralized exchanges need to pay trading fees for each transaction. The fee structures of crypto exchanges are typically volume-based, depending on the past 30 days' trading volume: the higher the past volume, the lower the trading fee. Our taker fees are based on a 20 million USD volume as the results show our arbitrage strategy could reach this trading amount. The taker-side trading fees at this volume level are 0.01% for Kraken, 0.02% for Bitstamp, and 0.0375% for BinanceUS[11]. Therefore, the total trading fees are the sum of two exchanges as we are taking orders in both exchanges, which is 0.03% for trading between Kraken and Bitstamp, 0.0475% for trading between Kraken and BinanceUS, and 0.0575% for trading between Bitstamp and BinanceUS. To cover these fees and make a profit, we preset our thresholds to match the trading fee for each exchange pair, and we only detect mispricing with price difference exceeding these trading fees.

Another arbitrage constraint is the time duration of mispricing. If it lasts too short, arbitrageurs are not able to identify and exploit it. Marshall et al. (2013) preset a pretty conservative threshold for duration when exploit mispricing in ETF market, which is 15

[11] Check on their websites: https://www.bitstamp.net/fee-schedule/, https://www.kraken.com/features/fee-schedule, https://www.forbes.com/advisor/investing/cryptocurrency/binance-us-review

seconds. However, we argue that threshold from over ten years ago is too conservative in today's high speed cryptocurrency market. Kraken claims that over 25% of all trading have latency less than 2.3ms, and 99% tradings have latency under 30ms in 2023[12]. Aleti & Mizrach (2021) found that 8% Bitcoin orders on Bitstamp are done in 50ms. Based on the fast speed of these exchanges, we think 1 second is a safe duration even after considering the different location of servers of different exchanges. Alsayed & McGroarty (2013) find the lead lag of information between S&P 500 and DAX future markets is about 300 milliseconds cross, proving 1 second is sufficient for information to go round. Therefore, we think arbitrage opportunities can be exploited if mispricing persists for more than one second, we set our threshold at 1 second and any mispricing that lasts less than this duration is not considered in our case.

Therefore, the identification of mispricing that could be identified as an exploitable arbitrage opportunity should satisfy following standards:

1. Bid price in one exchange is greater than ask price in another exchange, and the difference must exceed our preset threshold to make profit.

2. The mispricing lasts for over 1 second to allow arbitrageurs to identify and exploit it.

3. The actual arbitrage trade occurs at the first set of quotes for each tokens that appear 1 second after the potential mispricing is identified. We take all the available volume when executing arbitrage trading.

Therefore, our algorithm is:

$$\frac{B_{j,t}}{A_{i,t}} - 1 \geq T_{i,j} \quad \text{or} \tag{3.1}$$

$$\frac{B_{i,t}}{A_{j,t}} - 1 \geq T_{i,j} \tag{3.2}$$

$A_{i,t}$ and $B_{i,t}$ are the best ask and bid price of exchange i at time t, $A_{j,t}$ and $B_{j,t}$ are the best ask and bid price of exchange j at time t, $T_{i,j}$ is our preset threshold between exchange i and j.

Then the profit rate of two scenario arbitrage opportunity is:

[12] https://blog.kraken.com/crypto-education/performance-at-kraken

$$P_1 = \frac{B_{j,t}}{A_{i,t}} - 1 - F_{i,j} \qquad \text{or} \tag{3.3}$$

$$P_2 = \frac{B_{i,t}}{A_{j,t}} - 1 - F_{i,j} \tag{3.4}$$

where P_1 is the profit rate of eq (3.1), and P_2 is the profit rate of eq (3.2), $F_{i,j}$ is the trading fee between exchanges i and j. To ensure that the identified arbitrage opportunities are genuinely profitable, we only consider those that yield a minimum profit rate of 0.01% after accounting for transaction costs.

3. 4. 2. Determinants of mispricing

After detecting the existence of mispricing of stablecoin, we are going to analyze the daily market characteristics and figure out the determinants of arbitrage appearance and profitability. According to Marshall et al. (2013), short-lived mispricing is not likely to be driven by asymmetric information. O'Hara (2015) points out during present era of high-frequency trading, being informed means seeing and acting faster on price, order flows, liquidity and other factors that build so-called market microstructure. In this part, we focus on how factors of market microstructure impact the occurrence and profitability of mispricing. First, we analyze determinants of arbitrage appearance and profit through regression with daily data. Following the methodology in Marshall et al. (2013), we examine how market microstructure factors, including bid-ask spread and order flow factors affect the occurrence and profit rate of mispricing in daily-frequency, as these factors are the most representative factors of market microstructure (Amihud and Mendelson., 1986; Karpoff, 1987; Madhavan et al., 1997; Lee & Swaminathan, 2000;).

The analysis is as following regression 3.5 and 3.6. Regression 3.5 tests the determinants of instances of arbitrage while regression 3.6 tests the determinants of profitability. In equation 5, we use logit regression regressing on daily stablecoins bid-ask spreads, trading volume and order imbalance in each exchange. In equation 6, daily arbitrage profit are regressed on same variables. Eq 3.5 and Eq 3.6 are as follows,

$$I_{Arbitrage,t} = \alpha_0 + \alpha_1 Spread_t + \alpha_2 Volume_t + \alpha_3 Oib_t + \epsilon_t \tag{3.5}$$

$$profit_t = \beta_0 + \beta_1 Spread_t + \beta_2 Volume_t + \beta_3 Oib_t + \epsilon_t \tag{3.6}$$

Where a binary variable $I_{Arbitrage,t}$ that equals to 1 when an arbitrage opportunity is detected on day t and 0 otherwise. $profit_t$ denotes sum of profit rate of arbitrage opportunities on day t. $Spread_t$, $Volume_t$, Oib_t represent daily average bid-ask spread, trading volume and order imbalance, respectively. Spread is the average quoted spreads over time throughout the trading day of each stablecoin in each exchange, trading volume is daily trading volume, order imbalance is calculated as the daily difference between buyer-initiated trades and seller-initiated trades divided by the sum of the two.

3. 4. 3. Intraday market microstructure analysis

Then, to investigate the intraday market characteristics, we consider market microstructure factors immediately before, during, and after each arbitrage opportunity arises. We calculate each variable at the time of event, t_0 and $t_1$denote the starting time and ending time of each arbitrage opportunity. Time $t_0 - 1$ denotes the start of the one minute prior to the arbitrage opportunity starting minute t_0, $t_0 - 2$ denotes the previous minute before $t_0 - 1$, and so on. We calculate market characteristics variables on event days and at the same time of day on previous 20 trading days, and calculate the difference between value of variables on the event day and the average value of variables on previous 20 days. We are going to calculate variables during a pre-event period of $[t_0 - 5, t_0 - 2]$, an on-event period of $[t_0 - 1, t_1 + 1]$, and a post-event period of $[t_1 + 2, t_1 + 5]$. On this more granular scale, we measure market microstructure variables including bid-ask spread, market depth, order imbalance, trading volume and return standard deviation. According Marshall et al. (2013), this approach allows us to observe how market microstructure factors change when arbitrage opportunities arise, providing insight into the differences in prevailing trading conditions between mispricings and normal periods.

According to Goyenko et al (2009), in this part, spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Market depth is the value of shares at the first level (both the bid and ask) of limit order book at the start of each period. Order Imbalance is calculated as the difference between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval (Lee and Ready, 1991). The Return Standard Deviation is calculated based on the standard deviation of trade returns in each interval. Trading Volume is the total volume of trades in each period.

3. 5. Empirical result

3. 5. 1. Mispricing duration and profit

The results for the duration and profit of mispricings are presented in Table 3.3. Table 3.3 clearly shows that a massive number of mispricings of USDT and USDC among three cryptocurrency exchanges are detected, where there are over 20,000 mispricings of USDT and 50,000 mispricings of USDC are found during sample period. Also, it shows more mispricings are detected between Kraken and Bitstamp, while the fewer mispricings occurred between Kraken and BinanceUS.

Additionally, to examine if the validness of our strategy is impacted by the market shock and if these arbitrage opportunities only occurs during extreme market, we then present the distribution of mispricings by month in Appendix B.1. It shows that the during market shocks period and aftermath, frequency of mispricing did increase, but mispricings can be detected in every month of sample period, which suggests the effectiveness of our arbitrage strategy is not impacted by the crisis events. Specifically, November 2022 has most mispricings among all months during sample period, corresponding to the period of the FTX collapse. From May to August, when Terra crashed and afterwards, the number of mispricings in each combination of exchanges are much higher than from January to April. This indicates that these two events in the cryptocurrency market had a significant impact on stablecoins. Especially, Appendix B.1 shows that most mispricings between Kraken and BinanceUS were detected in May and November 2022 and March 2023, while in other months, the prices of stablecoins on Kraken and BinanceUS were relatively stable, with fewer mispricings detected. However, between Kraken and Bistamp as well as between BinanceUS and Bitstamp, mispricings allowing arbitrage are largely existed before May, which suggests that our results are not biased because of these two events.

This increased market inefficiency and mispricings during episode of volatility might be due to two reasons. First one is delayed price adjustments. During episode of volatility, price adjusts are more frequent than usual, and different crypto exchanges and market participants react to new information at varying speeds. This asynchronous adjustment to new information leads to mispricing, particularly during periods of rapid information flow (Chakrabarty et al., 2012; Menkveld, 2013). Another reason might be the decreased liquidity. During volatile period, market depth is high likely to decrease as some participants, especially market makers, will withdraw from trading to avoid risk (O'Hara, 2003; Anand and Venkataraman, 2016). And with lower liquidity, even relatively small trades can lead to significant price movements, causing mispricings (Amihud and Mendelson, 1980).

Also, we investigated the opening and closing of each mispricing and we find these mispricings are more correlated with Bitstamp. It shows that over 90% of arbitrage opportunities are opened and closed by orders from Bitstamp, which indicates that the price deviation and available orders of stablecoins in Bitstamp are more significant than that in other sampled exchanges.

Also, table 3.3 shows the profit rate of arbitrage opportunities after covering trading fees, we only investigate arbitrage opportunities with profit rate over 0.01% after covering trading fees. In each scenario, the minimum profit rate is 0.01% after covering transaction cost while the maximum profit rate is up to 1.9% for one single arbitrage opportunity. The positive profit rate of mispricing in each scenario is significant, indicating the cross-exchanges mispricing of stablecoin are profitable and exploitable.

As can be seen in Table 3.3, the net profit rates are positive after covering trading fees, indicating these mispricings are economically exploitable and genuine. In efficient markets, transaction costs typically eliminate small price differentials, ensuring that arbitrage opportunities cannot be exploitable or could only earn normal profits to compensate the risks (Fama 1970). However, the results contradicts the implication of EMH (Fama, 1970), while suggesting that arbitrage opportunities could exist and profitable in stablecoin markets as AMH implies (Lo, 2004). The results highlight temporary violations of the law of one price, and the inefficiencies in stablecoin markets. The fact that our results show positive arbitrage profit indicates that these market frictions, mainly trading fees, are not sufficient to erase all pricing discrepancies.

It is worth noting that the profit rate we document is highly dependent on trading fees between exchanges. We then conduct a sensitivity analysis to see how trading fees of exchanges could impact profit and frequency of mispricings. Following Lin and Tan (2023), we evaluate the net profit of mispricings under different level of transaction cost, and these results are reported in Appendix B.2. Appendix B.2 shows the frequency and net profit of mispricing between Kraken and Bitstamp as well as Bitstamp and BinanceUS. In general, Appendix B.2 shows that the reduction of transaction cost significantly improves the return and frequency of arbitrage opportunities. More importantly, the results indicate that even with highest level of transaction cost, there are still mispricings that are exploitable with positive profit. Notably, due to the volume-based fee structure of crypto exchanges, it is reasonable that institutional traders, with higher trading volume and lower transaction cost, are able to make higher profit than retail investors.

Also, the summary statistics for the length of time of arbitrage opportunities are presented in Table 3.3. Each duration is measured as the period of time that divergent pricing exceeds trading cost. As mentioned before, only mispricings that last for over 1 second will be detected, to ensure it is a conservative indication of the length that an arbitrageur needs to actually exploit the opportunity. As can be seen in Table 3.3, these mispricings are removed relatively quickly, where the mean durations of arbitrages in each scenarios are ranging from 24s to 157s. Moreover, the median duration of mispricings across different scenarios ranges from 5 to 33 seconds, the 75th percentile for each type of mispricing remains below 127 seconds, and the longest mispricing lasts less than one hour.

The rapid removal of arbitrage opportunity in stablecoin market is quite different to the results of the majority of prior studies on arbitrage in equity and other cryptocurrency markets that mispricings can last for a long time. For example, mispricings allowing arbitrage can exist in dual-listed stocks market (Froot and Dabora, 1999; Mitchell et al., 2002; Schultz and Shive, 2010) and cryptocurrency market for months and even over a year (Makarov and Schoar, 2020; Crépellière et al., 2023). Even between stablecoin primary and secondary market, the duration of mispricings can exist for over ten days (Lyons and Viswanath-Natraj, 2023).

Table 3.3. Arbitrage profit and durations

		N	Min	25 Per	Median	Mean	75 Per	Max	Std Dev
Panel A : Kraken overpriced/Bitstamp underpriced									
US DT	Profit	1843	0.010%	0.023%	0.037%	0.062%	0.057%	1.79%	0.043%
	Duration	1843	1	8	33	106	127	1576	136
US DC	Profit	2602	0.010%	0.019%	0.032%	0.053%	0.072%	1.98%	0.023%
	Duration	2602	1	3	19	132	81	2626	281
Panel B :Bitstamp overpriced/Kraken underpriced									
US DT	Profit	1991	0.010%	0.023%	0.031%	0.042%	0.049%	0.637%	0.051%
	Duration	1991	1	4	12	56	54	782	164
US DC	Profit	2973	0.010%	0.015%	0.022%	0.040%	0.082%	0.770%	0.031%
	Duration	2973	1	3	7	39	14	3223	414
Panel C :Kraken overpriced/BinanceUS underpriced									
US DT	Profit	102	0.010%	0.020%	0.021%	0.032%	0.031%	0.189%	0.034%
	Duration	102	1	6	21	75	77	605	122
US DC	Profit	25	0.019%	0.020%	0.029%	0.061%	0.055%	0.280%	0.075%
	Duration	25	1	3	6	81	123	565	156
Panel D:BinanceUS overpriced/Kraken underpriced									
US DT	Profit	227	0.010%	0.020%	0.029%	0.051%	0.061%	0.430%	0.066%
	Duration	227	1	2	5	24	23	319	50
US DC	Profit	32	0.010%	0.019%	0.020%	0.041%	0.050%	0.17%	0.042%
	Duration	32	1	5	20	74	121	371	101
Panel E :Bitstamp overpriced/BinanceUS underpriced									
US DT	Profit	2214	0.010%	0.017&	0.029%	0.042%	0.046%	0.580%	0.047%
	Duration	2214	1	4	26	117	89	2646	295
US DC	Profit	976	0.011%	0.014%	0.019%	0.029%	0.031%	0.750%	0.045%
	Duration	976	1	3	13	83	65	1561	184
Panel F :BinanceUS overpriced/Bitstamp underpriced									
US DT	Profit	2090	0.01%	0.018%	0.029%	0.044%	0.075%	1.83%	0.235%
	Duration	2090	1	7	29	115	103	1834	221
US DC	Profit	1606	0.01%	0.014%	0.021%	0.037%	0.039%	1.95%	0.037%
	Duration	1606	1	3	12	157	89	3243	408

Table 3.3 presents the distribution of profit and duration of mispricing in each scenario. The data is collected from the Thompson Cryptotick and the results relate to the January 1st 2022 – June 30th 2023 period. The profit rate is after considering transaction cost, we investigate all arbitrage opportunities that could generate at least 0.01% profit rate. All profits are in percent and durations are in seconds.

On the contrary, we suggest the relatively rapid removal of mispricings within stablecoin secondary market is consistent with the case in Alsayed and McGroarty (2012) that stock-ADR mispricing reduces by half in around 7 min, Busse and Green (2002) that price deviations in the stock market converge to an efficient level within 1 to 15 minutes following CNBC reports. Moreover, Chordia et al. (2005) find that it takes up to 60 minutes for mispricing to be corrected following order imbalances, Marshall et al. (2013) find mispricings allowing for arbitrage in the ETF market last only around 2 minutes on average. We suggest our results in stablecoin market is align with these empirical evidences that the mispricings are quickly removed, which implies investors who want to pursue the arbitrage opportunities are able to do so in stablecoin market, which is consistent with the presence of arbitrageur in stablecoin market (Lyons and Viswanath-Natraj, 2023).

These short-lived arbitrage opportunities in stablecoin markets lend support to the Adaptive Market Hypothesis (AMH) of Lo (2004), where the implication of evolutionary processes can help to explain the frequent mispricings and their quick removal. In our study, the divergents in pricing are quickly corrected and return to equilibrium. This rapid adjustment process is the hallmark of the AMH (Sulima, 2021; Shi and Zhou, 2017), as it illustrates how market participants respond to inefficiencies and contribute to the overall market efficiency. Also, the increased arbitrage potential during crisis events in May 2022, November 2022 and March 2023 also fits with AMH, as crisis events disrupt the normal functioning of markets, leading to more frequent deviations from expected pricing behavior and thus temporary inefficiencies. And these inefficiencies in price peg are removed quickly by arbitrageurs. Under the AMH, the documented arbitrage returns may represent occasional but economically meaningful profits. These profits not only help sustain the operation of market participants who actively monitor and exploit inefficiencies, but also serve as a form of compensation for their contribution to improving market efficiency.

However, the existence of arbitrage opportunities does not imply that arbitrage is always frictionless or fully exploitable in practice. There are some limits to arbitrage that might prevent arbitrageurs from correcting the mispricings as almost all arbitrage is not costless and riskless (Shleifer and Vishny, 1997; Mitchell et al., 2002). In implementing this arbitrage strategy, market participants may encounter substantial trading and information acquisition costs. According to the fee structures of major centralized exchanges such as Kraken, Bitstamp, and BinanceUS, trading fees are primarily determined by the participant's trading volume over the previous three days. As a result, retail arbitrageurs with relatively low trading volumes broadly face higher fees, which may reduce or eliminate the profitability of exploiting small mispricings. In addition, information acquisition costs represent another significant limitation. The arbitrage opportunities identified in this study are typically short-lived and require rapid detection and execution. As noted by Grossman and Stiglitz (1976, 1980), acquiring and processing market information is inherently costly, and arbitrageurs must be compensated for the role they play in restoring price efficiency. Similarly, Chen et al. (2020) emphasize that market efficiency is closely linked to the cost of acquiring timely and accurate information. Therefore, according to the literature, these high trading and information costs might be limits that prevents arbitrageurs from acting on small mispricings, particularly when the expected returns are insufficient to cover these frictions. However, in our case, information acquiring cost is minimal as many database and crypto exchanges offer free API to get real-time market data.

In addition, convergence risk is an important limit to arbitrage (Marshall et al., 2013). It refers to the uncertainty regarding when, or even whether, a mispricing will be corrected. In other words, simply identifying and trading on mispricings does not guarantee that profits will be realized promptly or at all, as as "the market can stay irrational longer than you can stay solvent"[13]. Moreover, inventory risk poses another constraint in the context of stablecoin arbitrage. This risk arises when arbitrageurs need to hold an asset while waiting to complete the arbitrage process, during which period the price may move adversely. In the case of centralized crypto exchanges, the limits and high cost of shorting selling in centralized crypto exchanges require arbitrageurs to pre-fund accounts with both USD and stablecoins. This need to maintain positions over time increases exposure to inventory risk.

However, we argue that both convergence risk and inventory risk are negligible in the context of our study. We are tracking identical assets across exchanges, which absolutely avoids the convergence risk. Also, as the sampled stablecoins in our case are all fully backed by reserves and are designed to maintain a one-to-one peg to the US dollar, which indicates that stablecoins prices are not likely to significantly move unfavorably. Therefore, the risk of adverse price movement while holding inventory is minimal because stablecoin prices rarely deviate substantially from their peg.

Finally, it is important to acknowledge that there may be additional costs or risk factors that remain unidentified or unexplored in the existing literature (Marshall et al., 2013). As such,

[13] http://www.maynardkeynes.org/keynes-the-speculator.html.

the observed profits might not only need to compensation for these observable frictions, but also for these unquantified risks that arbitrageurs might come across.

3. 5. 2. Determinants of mispricing

We then further analyze the determinants of mispricing occurrence and profit rate on daily basis by running regressions (3.5) and (3.6). The results relating to the determinants of arbitrage instances and the magnitude of arbitrage profits are presented in Table 3.4. Panel A presents the determinants of mispricing allowing arbitrage occurrence, showing the results of regression (3.5) and Panel B presents the determinants of arbitrage profit, showing the results of regression (3.6).

As can be seen in Table 3.4, it is clear that trading volume is positively correlated with both the occurrences and the profitability of arbitrage opportunities, while order imbalance is negatively correlated with them. However, the bid-ask spreads do not show a clear or significant relationship with either the occurrence or the profitability of arbitrage opportunities. The results in Panel A demonstrate that arbitrage opportunities are more likely to occur on days with higher trading volume. Furthermore, the significant and negative coefficients of order imbalance in Panel A indicates that there is a significant negative relationship between the instance of arbitrage opportunities and order imbalance, suggesting that arbitrage opportunities are more likely to occur when market is facing one-sided selling pressure. The daily bid-ask spreads on Kraken or Bitstamp do not appear to influence the occurrence of arbitrage opportunities. Panel B shows that arbitrage profits tend to be higher during periods of increased market activity, and that selling pressure may contribute to higher daily arbitrage profits. Similarly, there is no significant relationship between the bid-ask spread and either the occurrence or profitability of arbitrage opportunities on a daily basis.

The additional results from regressions 3.5 and 3.6 for USDT and USDC of other exchange combinations are presented in Appendix from B.3 to B.7. These results largely show similar patterns to those in Table 3.4, where trading volume is positively correlated with both the frequency of arbitrage opportunities and profitability, and order imbalance is negatively correlated with both. However, in some cases, there is a positive relationship between the bid-ask spreads and both the frequency and profitability of arbitrage opportunities, particularly in the mispricing between Kraken and BinanceUS. This indicates that arbitrage opportunity is more likely to occur and profits tend to be higher when bid-ask spreads in the limit order book are wider. The vague relationship between bid-ask spreads and the arbitrage instance or profitability in daily basis requires a more granular analysis, and the further relationship will be explored in the subsequent intraday analysis.

To ensure the robustness of our results, we re-estimate regressions (3.5) and (3.6) using subsample datasets from three crisis periods—May 2022 (Terra crash), November 2022 (FTX collapse), and March 2023 (SVB bankruptcy). The results remain consistent with those from the full sample.

Table 3.4. Determinants of Instances of Arbitrage and Arbitrage Profits of USDT.

		K-overpriced, Bit-underpriced	K-underpriced, Bit-overpriced
Panel A: Determinants of Instances of Arbitrage			
Kraken	Spread	-2.85	2.36
	Trading volume	7.31***	4.01***
	Order imbalance	-2.83***	-2.79***
	Adjusted R-square	0.04	0.06
Bitstamp	Spread	23.42	11.32
	Trading volume	10.84***	6.63***
	Order imbalance	-1.44***	-1.94***
	Adjusted R-square	0.10	0.13
Panel B: Determinants of Arbitrage profits			
Kraken	Spread	0.098	0.005
	Trading volume	0.531***	0.239***
	Order imbalance	-0.066**	-0.027***
	Adjusted R-square	0.304	0.148
Bitstamp	Spread	-0.043	-0.041
	Trading volume	0.248***	0.145***
	Order imbalance	-0.026**	-0.015**
	Adjusted R-square	0.265	0.153

Table 3.4 shows the results of regressions of determinants of arbitrages of USDT between Kraken and Bitstamp on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependent variable that equals one on days an arbitrage opportunity is created and zero otherwise. K-overpriced (Bit-overpriced) denotes USDT in Kraken (Bitstamp) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

3. 5. 3. Intraday market characteristics analysis

Then following the approach in Marshall et al. (2013), we turn our attention to considering intraday market characteristics changes at each mispricing. We calculate each variable at the time of the mispricing allowing arbitrage, t_0 and t_1 denote the starting time and ending time of each arbitrage opportunity. Time $t_0 - 1$ is the start of the minute prior to the arbitrage opportunity starting, $t_0 - 2$ is the previous minute of $t_0 - 1$, and so on. We measure each variable around each arbitrage opportunity and that at the same time of the day on the previous 20 trading days without mispricing. Then we calculate the percentage changes between the mean of variables during arbitrage opportunities and the mean of variables on the previous 20 days. We are going to calculate three periods around each arbitrage opportunity, a pre-event period of $[t_0 - 5$ to $t_0 - 2]$, an on-event period of $[t_0 - 1$ to $t_1 + 1]$, and a post-event period of $[t_1 + 2$ to $t_1 + 5]$. In this more microscopic scale, we consider market microstructure variables including bid-ask spreads, market depth, order imbalance, trading volume and return standard deviation. Since we need to calculate variables from 5 mins before mispricing starting to 5 mins after it ending, any mispricing that occurred within ten minutes will be considered into one to avoid overlap of period. The results of USDT market characteristics changes during mispricing between Kraken and Bitstamp are presented in Table 3.5. Additional results are demonstrated from Appendix B.8 to B.12.

Table 3.5 results show the market characteristics changes of mispricing and non-mispricing period of USDT between Kraken and Bitstamp. Panel A shows the changes of market characteristics when USDT in Kraken (Bitstamp) is overpriced (underpriced); Panel B shows the changes of market characteristics in opposite scenario. Table 3.5 indicates the factors of microstructure changes drastically around arbitrage opportunities than the equivalent time of day in the prior 20 trading days. Specifically, it shows that bid-ask spreads increase in both Kraken and Bitstamp throughout from pre-event period to post-event period.

Table 3.5. Market characteristics of USDT between Kraken and Bitstamp.

	Kraken			Bitstamp		
	t_0-5 to t_0-2	t_0-1 to t_1+1	t_1+2 to t_1+5	t_0-5 to t_0-2	t_0-1 to t_1+1	t_1+2 to t_1+5
Panel A : Kraken-overpriced, Bitstamp-underpriced						
Spread	**37.4%*** **	**38.5%*** **	**31.1%*** **	**173.6%*** **	**194.8%*** **	**162.1%*** **
Depth	**-43.7%*** **	**-44.6%*** **	**-44%*** **	**-37.6%*** **	**-37.3%*** **	**-55.9%*** **
OIB	-8.4%*	-7.2%***	-9.7%**	-5.1%	7.0%***	**14.6%*** **
Trade volume	**105.4%*** **	**214.2%*** **	**87.8%*** **	**198.2%*** **	**251.0%*** **	**201.5%*** **
Return std	**16.8%*** **	**18.7%*** **	**19.2%*** **	**461.8%*** **	**807.7%*** **	**591.2%*** **
Panel B : Kraken-underpriced Bitstamp-overpriced						
Spread	5.2%**	7.5%***	**18.8%*** **	**78.9%*** **	**83.6%*** **	**80.2%*** **
Depth	**-22.1%*** **	**-24.1%*** **	**-23.4%*** **	**-28.6%*** **	-8.2%***	**-44.0%*** **
OIB	-0.7%	1.9%	4.9%**	-5.2%*	**-14.0%*** **	**-16.8%*** **
Trade volume	**45.8%*** **	**115.6%*** **	**61.3%*** **	**277.7%*** **	**1532.7%*** **	**209.8%*** **
Reture std	8.3%	**13.3%** **	**18.3%** **	**520.8%*** **	**417.1%*** **	**362.3%*** **

This table presents percentage increases (positive) and decreases (negative) based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

In Kraken, spreads are significantly higher during the while window (minute -5 to 5) than the equivalent time of day in the prior 20 trading days. Particularly, when USDT in Kraken (Bitstamp) is overpriced (underpriced), spreads in Kraken are 31.1% to 38.5% higher. When USDT in Kraken (Bitstamp) is underpriced (overpriced), bid-ask spreads in Kraken during the whole window (minute -5 to 5) increase 5.2% to 18.8%. In Bitstamp, bid-ask spreads also significantly increase at mispricings, and the increments are even larger than that in Kraken. When USDT in Kraken (Bitstamp) is overpriced (underpriced), bid-ask spreads are 162.1% to 194.8% larger; when USDT in Kraken (Bitstamp) is underpriced (overpriced), they are 78.9% to 83.6% larger. The changes in bid-ask spreads during the whole mispricing periods suggest that increasing in bid-ask spreads might contribute to the arise of mispricing, providing evidence of a positive correlation between mispricing instances and bid-ask spreads in more granular analysis.

Additionally, Table 3.5 presents that mispricings usually come with decreasing in market depth. Market depth of USDT in both Kraken and Bitstamp are significantly lower not only during on-event window (minute -1 to 1), but also during the whole windows (minute -5 to

+5). During on-event period (minute -1 to 1), the percentage of market depth reduction in Kraken are 24.1% and 44.6%, and the percentage of market depth reductions in Bitstamp during on-event period are 8.2% and 55.9%. The significant increase in bid-ask spreads and decreasing in market depth during pre-event period (minute -5 to -2) indicates that market liquidity might drive the cross-exchanges mispricings. Also, the decrease of market depth and increase in bid-ask spreads during post-event period (minute 2 to 5) suggest that the arbitrage tradings might impair the market liquidity, we will discuss these in more detail below.

Changes in order imbalance are relatively smaller than that of bid-ask spreads or market depth, but most of them are significant and demonstrate contributions to removing mispricing, especially in Bitstamp. Order imbalance in Kraken is 7.2 % lower during the on-event window (minute -1 to +1) when USDT in Kraken (Bitstamp) is overpriced (underpriced), suggesting a stronger selling pressure to overpriced USDT. Similarly, in this scenario of mispricing, order imbalance in Bitstamp is 7.0% higher during on-event (minute -1 to +1) window, showing an increasing buying pressure to underpriced USDT. The results indicate order imbalance is contributing to converge the price deviation between two exchanges. On the other hand, when USDT in Kraken (Bitstamp) is underpriced (overpriced), the changes of order imbalance in Kraken is not significant, but the order imbalance in Bitstamp shows a significantly intensified selling pressure to overpriced USDT during on-event window (minute -1 to 1), which is 14% lower. The order imbalance changes presented in Table 3.5 are largely showing an increasing buying pressure to underpriced USDT and an intensified selling pressure to overpriced USDT, indicating order imbalance contributes to the removal of mispricings. The results are also consistent with existence of arbitrageurs within stablecoin secondary market, indicating arbitrageurs who want to exploit cross-exchanges mispricings are able to do so. Also, our results provide empirical evidence that arbitrage in stablecoin market is beneficial to the price stability (Pernice, 2021; Lyons and Viswanath-Natraj, 2023). Contrary to Jin (2021) who argue cross-exchanges arbitrage cannot help to restore price deviation, the order imbalance and rapid-removal mispricings in our empirical studies show that stablecoin cross-exchanges arbitrages do contribute to the eliminating of price deviation between exchanges.

Trading volume in both the Kraken and Bitstamp increases during the whole period (minute -5 to 5) around mispricings. In both scenarios, trading volume in Kraken and Bitstamp at mispricings increase largely, especially during on-event period (minute -1 to 1). The increasing trading volume indicates market becomes more active during mispricing than non-event period. However, even though the trading volume increases, the liquidity still decreases as the bid-ask spreads go up and market depth goes down. Johnson (2008) points out that previous empirical studies find volume and liquidity (e.g. bid-ask spread) to be unrelated. Our results indicate the significant price distortion between the two exchanges occurs when both spreads and trading volume escalates with decrease of market depth, which may suggests massive arbitrage tradings that dry out liquidity of market (Foucault et al., 2017; Jin, 2021), we will discuss this in detail below.

We also find that return standard deviation increases both in Bitstamp and Kraken during whole period of mispricing. Arbitrage opportunities are more likely to be created when the market is volatile. Our findings are consistent with Deuskar & Johnson (2011) who show that unpredictable flow driven risk could explain most market variance, and Marshall et al. (2013) that return is becoming more volatile when market liquidity decrease. This could also help to explain the increasing mispricings allowing arbitrage when stablecoin is when market is at extreme volatility due to the crisis during May and November 2022. The results show arbitrage opportunity usually occur when price is at large volatility. The rest results of intraday market characteristics analysis during mispricings are demonstrated in Appendix from B.8 to B.12, which present a similar pattern as in Table 3.5.

The results of microstructure characters analysis indicates that order imbalance contributes to the removal of mispricings, however, the increasing bid-ask spreads and decreasing market depth during on-event (minute -1 to 1) and post-event (minute 2 to 5) suggest this removal of mispricings comes at the cost of temporarily drying up market liquidity. These dramatical changes of microstructure characters demonstrate a picture that when mispricing occurs, arbitrageurs take the top orders from limit order book which bring the mispricing, causing the increasing of bid-ask spreads and decreasing of market depth. Due to the massive arbitrage trades, the trading volume surges largely. Our results provide empirical evidence supporting the short-lived nature of mispricings and the contribution of order imbalance, suggesting that cross-exchange arbitrage can also eliminate mispricings, which contradicts Jin's (2021) conclusion.

The drastic changes in bid-ask spread, market depth, order imbalance, and return volatility around mispricings demonstrate that market microstructure conditions are central to the occurrence and removal of pricing deviations. A widening bid-ask spread reflects higher trading costs and compensation for adverse-selection or inventory risk (Glosten & Milgrom, 1985; Ho & Stoll, 1981), while declines in market depth signal thinner order books that heighten price sensitivity to trades. Order imbalances indicate one-sided trading pressure, consistent with their predictive role for short-term returns (Chordia, Roll & Subrahmanyam, 2000), and elevated volatility captures the heightened uncertainty and information asymmetry during dislocations (Kyle, 1985). These findings imply that mispricings are closely tied to liquidity provision, trading flows, and risk perceptions rather than being isolated anomalies. Their reversal following arbitrage further underscores that restoring normal microstructure conditions is essential for prices to converge back to equilibrium, aligning with theories of arbitrage as a stabilizing mechanism (Shleifer & Vishny, 1997).

So far, these bid-ask spread, depth, order imbalance, and return standard deviation results suggest that what might be called "microstructure factors" might be one source of mispricing that leads to arbitrage opportunity. According to Foucault et al. (2017), this arbitrage activity that depletes market liquidity in our case might be "toxic", and it is created because arbitrageurs' profits in these trades are obtained with stale quotes. Easley et al. (2012) claims that order is regarded as toxic when it adversely selects traders who may be unaware that they are providing liquidity at a loss. They suggest in this scenario, short-lived arbitrage opportunities might be caused by the asynchronous adjustments in asset prices following information arrival instead of price pressure.

Specifically, Foucault et al. (2017) claims that arbitrageurs can be harmful for other investors, depending on the cause of arbitrage opportunities. When arbitrage opportunities are due to temporary demand or supply shocks ("price pressures"), arbitrageurs implicitly act as liquidity providers by exploiting them (see. Gromb and Vayanos, 2002, 2010). However, short-lived arbitrage opportunities are also due to asynchronous adjustments in asset prices following information arrival. Arbitrageurs' profits in these trades are obtained at the expense of traders with stale quotes and thus high-speed arbitrageurs can harm market liquidity in this case by take the top orders of limit order book and wider the bid-ask spreads and lower the market depth (Copeland and Galai, 1983). In this scenario, slow traders are providing extra liquidity to the market at a loss, such as selling at a discount or buying at a premium. Arbitrageurs then match these orders, removing the mispricing and taking the extra liquidity at the same time, their profit are acquired at the expense of other traders. Therefore, following the approach of Chordia et al. (2005), we then conduct a impulse response function test to investigate if price discovery speed difference contributes to the arbitrage opportunities we document. The results are presented in Figure 3.1.

Fig 3. 1. Impulse Response Function: Response of exchanges to one unit of USDT market shock.

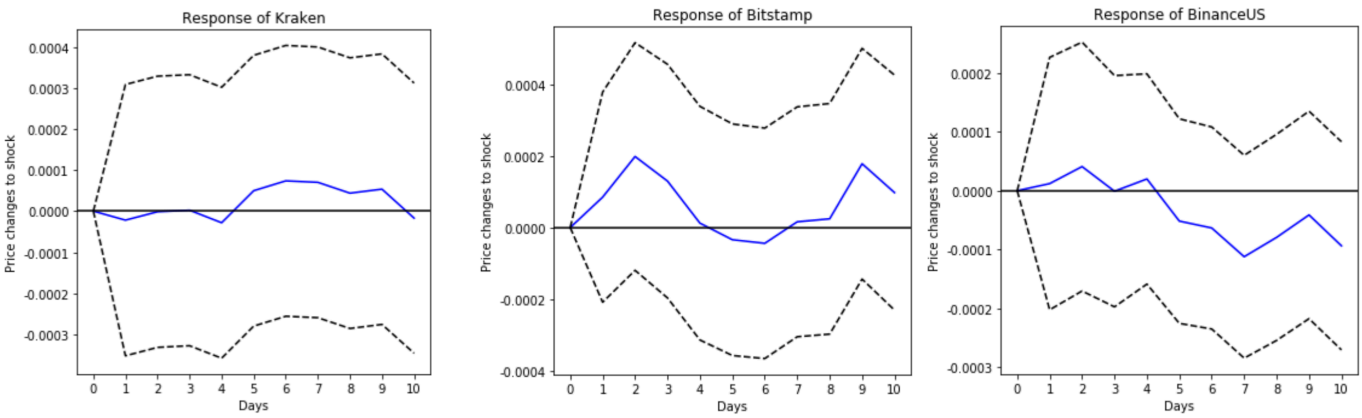


Figure 3.1 shows the results Impulse Response Function of each exchanges. It shows the response of USDT mid-quote price in each exchanges to one unit shock (one unit standard deviation) of daily market volatility of USDT. The results relate to the sample period from January 1st 2022 – June 30th 2023. The solid line is the mean result and the dashed lines represent the two-standard error bounds. These plot are generated from days there is mispricing generating arbitrage opportunities.

In Figure 3.1, we illustrate the response of USDT mid-quote price in each exchange to a standard deviation shock of one unit (one standard deviation) in stablecoin market volatility, over a 10-days period. These results are generated from days with mispricings. The daily USDT market price are collected from CoinMarketCap, which is calculated by taking the volume weighted average of all USDT/USD reported by each exchange[14], representing the the market price of USDT.

The results show different response speeds of USDT price in each exchanges to a market shock. Bitstamp reacts slower to market shock than other two exchanges while Kraken has fastest response. Specifically, once receiving shocks from market, it only takes 2 days for Kraken to its initial position, which is 0 in the y-axis, and BinanceUS takes 3 days to initial level while it takes 4 days for Bitstamp to get back to 0. These three exchanges have

[14] https://support.coinmarketcap.com/hc/en-us/articles/360015968632-How-are-prices-calculated-on-CoinMarketCap

different response speed to market shock, suggesting different price discovery. Additionally, the result that Bitstamp has slowest response to market shock with the fact that most arbitrage opportunities are opened and closed by orders from Bitstamp suggest differences in price discovery time between exchanges also contribute to mispricings we document, and this might be another source of cross-exchanges mispricing of stablecoin.

3. 5. 4. Robustness tests

To ensure the robustness of our results and to examine whether the identified arbitrage opportunities extend beyond sample period, we conduct an out-of-sample robustness check. Specifically, we collect USDT quotes data from Kraken and Bitstamp on the first day of each month in 2024 and assess the existence of cross-exchange mispricings allowing for arbitrage. Even after incorporating the highest trading fees, we identify 337 exploitable arbitrage opportunities over this 12 days, yielding potential cumulative profits exceeding $460. These results corroborate our main findings and provide additional evidence that stablecoin mispricings between exchanges are not confined to specific sample periods. The recurrence of arbitrage opportunities across time further suggests that such mispricings are persistent and potentially systematic.

3. 6. Discussions

Based on the arbitrage and microstructure theory (Ross, 1976; Kyle, 1985; Amihud and Mendelson, 1986;), we investigate the cross-exchanges mispricings of stablecoins and the prevailing market microstructure when mispricing is created. We detected mispricings that allow arbitrage, and their frequency, profitability and duration. The frequent and quickly removed arbitrage opportunities indicates the efficiency of stablecoin market evolves over time, suggesting AMH (Lo, 2004) in stablecoin market.

Also, our results show that the mispricings have enough profitability to cover the transaction cost across exchanges, bring profits to arbitrageurs. The profits generated from mispricings we document are not risk-free, however, we believe these risks of arbitrage, such as convergence risks and inventory risks are small enough to neglect in our case. Specifically, as short-selling is not allowed in these exchanges, arbitrageurs have to prepare a certain amount of stablecoins in advance, bringing them convergence risks and inventory risks. But due to the stability of stablecoins, we argue that the convergence risk and inventory risk are reduced to minimal. Additionally, although these arbitrage opportunities are quickly disappeared, indicating arbitrageurs face strong competitions and need to identify and execute these mispricings quickly, the results suggests the durations of arbitrage opportunities are long enough for arbitrageurs to exploit. Our results show that in real life market, arbitrage exists but is limited by factors including capital constraints, market conditions, and the behavior of other market participants, which is consistent with modern arbitrage theory and AMH (Lo, 2004; Shleifer and Vishny, 1997).

Furthermore, we also examine the prevailing market microstructures when mispricings are created. According to Marshall et al. (2013), we investigate the bid-ask spreads, market depth, order imbalance, trading volume and trade-to-trade returns, our analysis shows these microstructure factors change significant prior to the occurrence of mispricings. We find these microstructure factors such as liquidity, order imbalance could lead to temporary market inefficiency and might be one source of mispricings. These findings are consistent with previous theoretical work that market microstructure contributes to mispricing fits into emerging market like stablecoin market (Kyle, 1985; Hasbrouck, 1991). Our study also support the claims in previous theoretical works that market microstructure is a driver of market inefficiency, as reflected in the the occurrence of mispricings and arbitrage opportunities (e.g. Kyle, 1985; Hasbrouck, 1991; Grossman and Stiglitz, 1980; Black, 1986; De Long et al., 1990; Amihud and Mendelson, 1986).

Additionally, we generate an impulse response function test for stablecoin price in each exchange to a unit shock of stablecoin market. The results show that these exchanges respond to a market shock with different speed, suggesting that differences in price discovery times might be another drivers of the mispricings we document. Our finding proves that the asynchronous price discovery exists across different trading venues of stablecoins, and delays in information processing may lead to temporary misalignments in prices. Our studies provide empirical evidence to support the information dissemination theory in Hasbrouck (1995) that delays in information dissemination lead to price deviation in short term. According to Barclay and Hendershott (2003), increasing the price discovery speed of each exchange might mitigate the cross-exchanges mispricings of stablecoin.

Overall, our results show that stablecoin market fits into the theory of market microstructure and implications of AMH (Ross, 1976; Kyle, 1985; Amihud and Mendelson, 1986; Lo, 2004), which the market efficiency evolves over time and pretty much depend on market conditions, microstructure factors and price discovery.

3. 7. Conclusions

This chapter focus on cross-exchanges mispricings that allow arbitrage opportunities of stablecoins, we analyze the prevailing trading conditions when mispricings are created. We suggest these short-lived arbitrage opportunities are consistent with Adaptive Market Hypothesis (Lo, 2004), where the evolutionary processes of market conditions and efficiency are supportive to the implications of Adaptive Market Hypothesis. Our papers also show that the theory of arbitrage and the limits of arbitrage fits into stablecoin markets (Ross, 1976; Kyle, 1985; Amihud and Mendelson, 1986; Shleifer and Vishny, 1997; Mitchell et al., 2002).

Our research is based on the high-frequency tick-by-tick snapshot of limit order book data and trade datasets of USDT/USD and USDC/USD in three leading centralized exchanges. High frequency datasets allow us to capture quickly removed mispricings and evolving market microstructures. Also, USDT and USDC are suitable for this study as they are highly liquid, which are more liquid than an U.S stock and ETF. Having highly liquid assets in this study is important as it allows us to calculate meaningful statistics at high frequencies.

In addition, stablecoins are natural suitable for arbitrage studies for some reasons. First, fully-backed stablecoins are traded in multiple exchanges and totally identical in all of them, this character brings low fundamental risk; second, stablecoin are pegged to fiat currency, making the price deviation easy to observe; last, stablecoin providers have incentive to minimize tracking error so as to attract more users and holders which mitigates the risk that stablecoins will not go back to their peggings or not converge from mispricings, which reduces the convergence risk and inventory risk in the arbitrage setting.

We detected massive mispricings across centralized exchanges, which creates arbitrage opportunities within stablecoin secondary markets. We demonstrate that these mispricings could generate positive profits after considering transaction costs. Our sensitivity analysis shows that even under various level of transaction costs, these mispricings exist and are profitable for investors. The durations of arbitrage opportunities indicate that these mispricings are quickly corrected, but are persistent enough for arbitrageurs to exploit.

The prevailing market characteristics analysis suggests that market microstructure factors significantly contribute to the mispricing that enables arbitrage. We show that bid-ask spreads widen and market depth decreases during the windows when arbitrage opportunities occur, while trading volume and return volatility surge. Further Impulse response function analysis show that asynchronous price adjustments across exchanges might contribute to the observed mispricings.

To the best of our knowledge, chapter three is the first empirical study that focus on cross-exchanges mispricings of stablecoins. Our research provides a new arbitrage route and proves it is practical, which might help to remove smaller price de-pegging as Lyons and Viswanath- Natraj (2023) find more intensive arbitrage activity could reduce price deviation of stablecoins. Also, our research sheds light on the new factors that result in mispricings of fully-backed stablecoins. Understanding the mispricings of stablecoins is important for academic literature and also for the cryptocurrency industry sector and the financial regulators. Furthermore, as stablecoin is now becoming the most important medium of exchange in cryptocurrency market, its financial stability and market efficiency is vital to the whole market.

This study provides valuable implications for stablecoin issuers and cryptocurrency exchanges. For stablecoin issuers, the findings highlight the vulnerability of stablecoins price stability to large one-sided orders and liquidity shortages. This suggests a need to strengthen stability mechanisms. For crypto exchanges, our results suggest that improving the speed of price adjustment to new information could help reduce stablecoins mispricings and enhance market efficiency. Identifying more factors that lead to mispricing of stablecoin can equip stablecoin providers with more toolkits to prevent huge financial instability and provide more stability in the market. This is essential for protecting vulnerable stablecoin users who engage with crypto asset without sufficient background, knowledge and financial cushion to absorb the inherent volatility, and this is also crucial to keep promise of cryptocurrency that offering a stable financial system free from banks, a store of value and medium of exchange in daily payment.

Chapter 4

High-frequency Lead-Lag Relationships of Cryptocurrencies and Crypto Exchanges

Chapter 4

High-frequency Lead-Lag Relationships of Cryptocurrencies and Crypto Exchanges

Abstract

We investigate high-frequency cross-venue and cross-asset lead-lag relationships in the cryptocurrency market. Using tick-level snapshot of limit order book data, we demonstrate that lead-lag relationships of a few hundred milliseconds exist both across major centralized cryptocurrency exchanges and among different cryptocurrencies. Notably, in contrast to prior research, we find that Bitcoin occupies a lagging position at the high-frequency level, while Solana and XRP being leading assets among the sampled tokens. In terms of cryptocurrency exchanges, Bitstamp holds a relatively leading position, whereas Bitfinex tends to lag. Our analysis further reveals that market depth and order book resilience are correlated with lead-lag positions of cryptocurrencies. Furthermore, these rapid lead–lag relationships within the same exchange exhibit pronounced intraday patterns, diminishing during the opening hours of the U.S. stock market.

Key words: **Lead-Lag Relationships, cryptocurrency, crypto exchanges, Hayashi-Yoshida Estimator**.

4. 1. Introduction

Cryptocurrencies are digital currencies that are built on blockchain technology that allows verification of payments and other transactions in the absence of a centralized custodian. Originally introduced in a paper by Nakamoto (2008), Bitcoin becomes the most famous and earliest cryptocurrency. Since then, the market for cryptocurrencies has evolved dramatically. Cryptocurrencies have experienced rapid growth followed by substantial downturns in recent years. However, despite the original vision of decentralization that underpins cryptocurrency, cryptocurrencies have not fully achieved decentralization in practice as a major proportion of trading activity remains concentrated on centralized exchanges[15].

Today, over 250 centralized exchanges trade Bitcoin and other cryptocurrencies[16]. The majority of these centralized exchanges function like traditional equity markets where traders submit orders, and exchanges match these orders based on centralized limit order books. However, unlike equity assets, cryptocurrencies such as Bitcoin and Ethereum are broadly traded in a number of exchanges, these would bring lead-lag effect problem.

Lead-lag effects in financial markets describe situations where some financial assets are leading and provide information about the future price or other development of other assets lagging behind. The lead-lag effects emerge mainly due to different speed of price discovery in different market, which leading to short disequilibria (Lo, 2004; Theissen, 2016). These effects arise primarily from differences in the speed of price discovery across markets, resulting in short-lived disequilibria (Lo, 2004; Theissen, 2016). Such phenomena are particularly common in cryptocurrency markets, as tradings of one cryptocurrency usually occur across multiple venues and traders react to new information at varying speeds.

The lead-lag relationships in cryptocurrency market has been widely studied, where Bitcoin and Ethereum broadly proved at the leading positions in cryptocurrency market. Yarovaya and Zięba (2022) analyze the lead-lag relationship of top 30 cryptocurrencies, provide empirical evidence supporting that Bitcoin is at a leading position to nearly all cryptocurrency. Sifat and Shariff (2019) found bi-directional lead-lag effect between Bitcoin and Ethereum. Hyun et al. (2019)'s research confirms the leading positions of Bitcoin and

[15] https://coinmarketcap.com/charts/spot-market/

[16] https://coinmarketcap.com/rankings/exchanges/

Ethereum. However, these lead-lag relationships are not permanent, as Qureshi et al. (2020) find the switch in the lead and lag relationships of cryptocurrency returns, suggesting alternating time and frequency interdependencies.

The existing research on lead-lag relationships in cryptocurrency market are mainly conducted with relatively equally-spaced datasets, such as daily or hourly frequency (Qureshi et al., 2020; Makarov and Scholar, 2020;; Sifat et al., 2019), a few of them with 20 minutes or higher frequency (Yarovaya and Zięba, 2022). Specifically, Sifat et al. (2019) observe bi-directional relationships between hourly and daily transaction prices of Bitcoin and Ethereum. Schei and Rix-Nielsen (2019) investigate the high-frequency lead-lag relationship of Bitcoin in different exchanges.

We argue that previous existing research have limits in several aspects. First, these research are largely limited to Bitcoin, potentially overlooking other cryptocurrencies, especially for research focus on lead-lag relationship of same token across exchanges (Brandvold et al., 2015; Schei and Rix-Nielsen, 2019;). Second, the frequencies of datasets are relative low, mainly concentrated on daily data, which potentially miss fast lead-lag relationships. We argue that these research with low and equally-spaced frequency lead-lag relationship are not able to provide much information for practical tradings, as useful information for practical trading usually only lasts seconds or even sub-second and then becomes outdated in high frequency trading venue (O'Hara, 2015; Alsayed and McGroarty, 2014). O'Hara (2015) raises that with the emergence of algorithmic and high-frequency trading (HFT), the dissemination of information in financial markets has substantially changed and been speeded up. Alsayed and McGroarty (2014) show that algorithmic arbitrage brought by lead-lag price information rarely exist for longer than 300 milliseconds. In this context, lead-lag relationships with datasets that are sampled with equal frequency are hard to play an role in predicting price or building arbitrage strategy. Therefore, tick-by-tick data level lead-lag analysis is demanding for cryptocurrency market during this HFT period.

The tick data level lead-lag analysis in cryptocurrency market does not receive much attention yet. The rare and existed studies with tick-by-tick data only focus on Bitcoin, and overlook other leading cryptocurrencies(Anderson, 2023; Schei and Rix-Nielsen, 2019). Therefore, in existing literature, little attention has been given to the high-frequency, especially tick-level lead-lag effect in cryptocurrency markets. Understanding this is important, as only fast lead-lag relationship could provide valuable insights into actual trading and price discovery mechanism to cryptocurrency markets (O'Hara, 2015; Alsayed and McGroarty, 2014). If sub-second lead-lag relationships in cryptocurrency market are detected, trading strategies might be built relying on this fast relationships as tradings in centralized crypto exchanges could be executed within several milliseconds (Aleti & Mizrach, 2021).

To fill this research gap, our study aims to solve two research questions in this study (i) Do high-frequency lead-lag effects exist among same cryptocurrency across different exchanges? (ii) Do high-frequency lead-lag effects exist between cryptocurrencies in same exchange? To address these two research questions, we collect limit order book datasets and investigate the rapid lead-lag relationships among cryptocurrencies in same centralized exchanges, and rapid lead-lag relationships among centralized exchanges in terms of same cryptocurrencies.

Specifically, in this study, we consider four top cryptocurrencies — Bitcoin, Ethereum, Solana and XRP in three leading centralized exchanges — Kraken, Bitstamp and Bitfinex. To deal with the irregular tick data of limit order books snapshot from these centralized exchanges, we apply a recent advance in the statistical measurement of lead-lag relationships proposed and extended by Hayashi & Yoshida (2005) and Hoffman et al., (2013). This measurement enables us to analyze non-contemporaneous correlations of irregular tick datasets. Furthermore, we calculate the market depth and mid-price update frequency, trying to explain the factors that might affect the lead or lag positions of cryptocurrencies. In addition, we also split each trading days into 24 hourly interval to analyze the intraday pattern of the lead-lag effects.

Our study yields several important findings. First, our results suggest strong and fast lead-lag effects among different tokens and exchanges at high-frequency level, where the lag lengths are sub-second and up to 200 ms. Notably, contrary to previous studies that suggest Bitcoin holds the leading position in the cryptocurrency market (Anderson, 2023; Yarovaya & Zięba, 2022; Hyun et al., 2019), we observe that Bitcoin holds a lagging position at high-frequency level, where it shows that Bitcoin lags behind other sampled tokens on each centralized exchange. Additionally, we find that Bitstamp and Kraken hold relatively leading positions, while Bitfinex lags among the sampled exchanges. However, the lead-lag relationship between exchanges varies across different tokens.

Second, we find that market depth and order book resilience are correlated with the lead–lag positioning of cryptocurrencies traded on the same exchange. Specifically, our results show that cryptocurrencies with deeper market depth tend to exhibit greater order book resilience, characterized by less frequent mid-price updates and smaller responses to market shocks. These cryptocurrencies are more likely to occupy lagging positions in high-frequency lead–lag dynamics.

Lastly, our intraday pattern analysis suggests that the strength of lead-lag effects might be linked to the activity level of U.S. traditional financial markets. During the opening hours of U.S. stock markets, both the maximum correlations and the lead-lag length among cryptocurrencies reach their lowest levels of the day.

Our contribution is multifold. To the best of our knowledge, this is the first paper to investigate the high-frequency lead-lag relationships among centralized exchanges with multiple cryptocurrencies. We push beyond past work using high-frequency data focusing on lead-lag relationship of Bitcoin (Anderson, 2023; Schei and Rix-Nielsen, 2019), to more leading alt-coins. Our findings challenges previous views that Bitcoin is at the leading position in crypto market. (Anderson, 2023; Yarovaya & Zięba, 2022; Hyun et al., 2019), highlighting the different lead-lag dynamics of cryptocurrencies in high frequency scale.

As a further contribution, our research shed new light on the factors that might affect high frequency lead-lag effect in cryptocurrency market. Our results suggest that lead-lag positions might be correlated with market depth and order book resilience, and the active market and investors might reduce the lag length and lead-lag effect. Our study provides empirical evidences supporting that previous theoretical work on market microstructure could be applied into cryptocurrency market.

Our results have implications to cryptocurrency investors and centralized exchanges. The high-frequency lead-lag effects between cryptocurrencies and between exchanges in our research could provide investors information on forecasting possibility and accuracy of cryptocurrency price change, which could help investor build arbitrage strategy further as in traditional market (Alsayed and McGroarty, 2014; Huth and Abergel, 2014). For exchanges, this correlation between lag length and US equity market activity could give them insight that to attract more investors globally to avoid long lag-length seasonality and speed up the information transmission when US market is closed.

The remainder of the paper is structured as follows. Section 4.2 reviews related literature. In Section 4.3, we summarize sampled datasets used in the analysis. Section 4.4 illustrates methodology and models. In Section 4.5 we present empirical results. Section 4.6 is the discussions and section 4.7 is the conclusions.

4. 2. Related literature

Extensive research has focused lead-lag theory and empirical analysis due to the importance of the transmission of information and price discovery across assets and markets. This section will first introduce the definition and theory foundation of lead-lag effect, and then review the empirical research about lead-lag phenomenon on traditional financial markets as well as cryptocurrency markets. Based on previous research, we also discuss several factors that might affect the lead-lag effect. Additionally, this section outlines the common methodologies used to investigate lead-lag effects with different frequent dataset. Finally, this section briefly reviews the limited literature on lead-lag effect on cryptocurrency market, as well as the research gaps and our contributions to the literature.

4. 2. 1. Definition of lead-lag effect

The concept of lead-lag effect emerged in the context of the ongoing debate surrounding the efficient market hypothesis (EMH). The definition of lead-lag effect in finance refers to the phenomenon where the price movements of one financial asset precede and potentially influence the price movements of another asset. The essence of this definition lies in how fast markets participants react to the arrival of new information. If one market reacts faster to new information and the other one is slow to react, a lead-lag relationship will be observed (Chan, 1992).

However, at the beginning, the lead-lag effect was not taken and studied series, where it was thought a symptom of the so-called "non-synchronous trading" problem. The non-synchronous trading problem refers to the issue that prices are assumed to be recorded at fixed intervals when they are in fact recorded at intervals of varying lengths (Lo and MacKinlay, 1990). Fisher (1966) is the first to show that non-synchronous sampling of prices could result in misleading autocorrelation which may not exist. Cohen et al. (1986)

and Lo & MacKinlay (1989, 1990) show that lead-lag effect might be a consequence of non-synchronous trading.

The concept of the lead-lag effect has been explored by various researchers over the years, with significant contributions made in the context of price discovery and market dynamics. The earliest works in this area might be on the relationship between futures price and spot price (Zeckhauser and Niederhoffer, 1983; Kawaller et al., 1987). Cohen et al (1986) and Lo & MacKinlay (1989) proposed models trying to explain the lead-lag effect from the perspective of non-synchronous trading (thin trading).

One of the most influential works in this area is by Hasbrouck (1995), who established a framework for understanding the lead-lag relationships from the perspective of price discovery. He examined the contributors to price discovery across multiple markets, highlighting the impact of market microstructure factors on price discovery speed. Similarly, Theissen (2016) points out that price discovery is pretty much based on the adjustment of prices to market-wide information, and the assets or markets with low speed of price adjustment will be at lag positions. These asynchronous price adjustments lead to lead-lag effect and might thus bring arbitrage opportunities (Marshall et al., 2013; Alsayed & McGroarty, 2014).

Then, another important contribution came from Chan (1992), who examines several factors that might affect the lead-lag effect. He points out that the type of news (good or bad), intensity of trading activity and the market-wide movement are the determinants of lead-lag effects. Also, the short-sale constraints and the wide of information are also found affect the speed of adjustment of prices to new information, and thus to affect the lead-lag effect (Diamond & Verrecchia, 1987; Chan 1990).

4. 2. 2. Theory foundation of lead-lag effect

The theory foundation of lead-lag effect is pretty much based on Efficient Market Hypothesis (Fama, 1970) and adaptive market hypothesis (Lo, 2004), information diffusion theory and market microstructure theory.

Under Efficient Market Hypothesis (EMH) proposed by Fama (1970), prices should fully reflect all available information in efficient market. One important implication of EMH is that all relevant information is freely and instantly available to all market participants, ensuring no informational advantage (Fama, 1970). This implication is pretty much based on the prerequisite that new information could transmit into the whole market instantly. However, in practical market, information is not always distributed or processed instantaneously and simultaneously across markets, introducing the lead-lag effect. This prerequisite has been criticized because it takes time and cost to get information in market (Hong and Stein, 1999), as if all information were freely and instantly available and reflected in prices, there would be no incentive for investors to acquire information (Grossman & Stiglitz, 1976, 1980).

Then Lo (2004) proposed Adaptive Market Hypothesis (AMH), reinterprets traditional market efficiency theories within the framework of evolutionary principles, including implications about information and price discovery. AMH considers the role of market participants, suggesting that markets are not always efficient and that market conditions are dynamic. It highlights that these conditions largely depend on the behaviors of various market participants. Therefore, in this context, the lead-lag effect might exist because market participants adjust to the new information or changing conditions at different speeds (Theissen, 2016), leading to temporary disequilibria (Grossman & Stiglitz, 1976, 1980). The leading market is typically faster at incorporating new information. Additionally, these asynchronous price adjustments which lead to lead-lag effect usually cause market inefficiency, bringing arbitrage opportunities (Marshall et al., 2013; Alsayed & McGroarty, 2014).

The theory foundation of lead-lag effect is also correlated with Information Diffusion Theory. The theory's origins can be traced back to Everett Rogers' seminal work, "Diffusion of Innovations”[17], which provided a framework for understanding the spread of innovations (Rogers et al., 2014). The Diffusion of Innovations describe that market participants have different adjust speed to innovations such as new information or new technology. Hong & Stein (1999) improve the Information diffusion models, suggesting that investors do not immediately and simultaneously act on new information due to limits on attention or differing access to information. Barberis et al. (1998) proposed a model of of investor

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[17] The book "*Diffusion of Innovations*" by Everett M. Rogers was first published in 1962

sentiment, and they discusses how sentiment-driven trading contributes to the slow diffusion of information, supporting the idea that lead-lag effects can emerge due to heterogeneous beliefs and trading speeds.

Additionally, the theory of lead-lag effect is also inherently tied to the field of market microstructure, as both involve the mechanisms of market characteristics, information dissemination, and price formation. In terms of various factors of market microstructure, liquidity is the key factors of market characteristics that impact the information flow, which is essential to lead-lag effect. Previous papers find that assets or markets with greater liquidity and lower costs broadly lead their less liquid counterparts. Hasbrouck (1995) explores price discovery across multiple markets and highlights how liquidity and trading activity determine the contributions of each market to price discovery. Chordia & Swaminathan (2000) find trading volume is a significant determinant of the lead-lag patterns observed in stock returns, which is caused by the fact that the return of low volume portfolios respond more slowly to information in market returns. Chordia et al. (2008) provide evidence that when liquidity decreases in certain markets, the lead-lag effect increases.

Existing literature have a commonsense that assets with higher liquidity tend to have react to new information faster, and thus are more likely to lead the assets with lower liquidity (i.e. Huth and Abergel, 2014;). On the contrary, other literature found that assets with higher liquidity, especially deeper market depth, have the ability to absorb market shocks, which might makes them seem to react to new information slowly. Bhattacharya and Spiegel (1998) find that exchanges with higher liquidity have higher ability to absorb very large shocks. Menkveld and Zoican (2017) suggest that mid-price responsiveness is a function of liquidity and depth, highlight the interplay between latency (exchange speed) and liquidity provision is crucial in determining how quickly and efficiently prices adjust to new information. Bouchaud et al. (2009) also points out that the mid-price adjusts gradually to order flow, and the structure of the order book, such as market depth, plays a key role in determining the speed of price adjustment to new information. Degryse et al. (2005) also suggest that when assets with high liquidity are impacted by aggressive order flow, they have the ability to absorb market shocks, keeping mid-price stable. Our study contributes to this strand of literature by identify that market depth might be correlated with fast lead-lag relationships in crypto market.

Moreover, information asymmetry and market segment are also found correlated with lead-lag effect. Markets or assets with lower information asymmetry tend to incorporate new information faster, broadly lead those with higher information asymmetry (Glosten and Milgrom, 1985). Easley and O'hara (1992) discusses how information asymmetry affects price discovery, linking this to lead-lag effects in information incorporation. They found market segment could affect the information transmission and thus impact lead-lag effect. Eun and Shim (1989) examines global lead-lag effects in international stock markets, focusing on information transmission and market segmentation, they found the market segment could slow the information transmission and bring lead-lag effect.

4. 2. 3. Market activeness and lead-lag effect

The lead-lag effect tends to diminish when markets are more active while it is intensified when market is relative inactive (Chordia et al., 2011). Increased market activity broadly translates into higher trading volumes, greater liquidity, and faster information flow, which collectively reduce the delay in price adjustments between leading and lagging assets. And the lead-lag effect weakened due to faster information transmission, intensified arbitrage activity and more high-frequency-trading.

First, when markets are active, market liquidity tends to increase. Higher liquidity reduces the time it takes for information to be incorporated into prices. Trades with better information can be executed more quickly in a liquid market, leading to faster price adjustments (Kyle, 1985). This is due to lower transaction cost brought by narrow bid-ask spread allows prices to adjust more quickly (Amihud and Mendelson, 1986), and higher liquidity also allow traders to execute large orders, which are more likely to be informed, without significant delays (Grossman and Miller, 1988). Also, when market is active, it is broadly correlated with continuous trading, where prices adjust continuously as new information is disseminated, resulting in quicker price discovery (Biais et al.,1995).

Second, in active market, the lead-lag effects are diminished as arbitrage tradings are more intensive. By exploiting temporary price discrepancies between leading and lagging assets, arbitrageurs force prices to converge, integrating information and reducing inefficiencies

(Hasbrouck, 1995). More intensive arbitrage tradings in active markets could remove stale orders more quickly and diminish the lag length.

Third, during active periods, for example, during trading time of US market, more institutional and high frequency traders are active. These active high frequency traders amplify trading intensity in both leading and lagging markets. By exploiting millisecond-level price differences, they reduce the duration and magnitude of lead-lag relationships (Hasbrouck and Saar, 2013). Our study contributes to this strand of literature by examining the intraday lead-lag effect between cryptocurrency, and we find strong seasonality that the lead-lag effect diminished during the opening time of US stock market.

4. 2. 4. Empirical review

4. 2. 4. 1. Cryptocurrency

Our paper contributes to the growing body of literature that focus on cryptocurrency. Research on cryptocurrencies and especially in finance and economics is still in its beginning. Earlier, the majority of papers in this stream of literature focuses on the potential effects of cryptocurrencies as a payment and transaction mechanism. Prior studies provide a broad perspective on the economics of cryptocurrencies and the blockchain technology they are built upon (Ciaian et al., 2016; Harvey, 2016; Böhme et al., 2015; Raskin and Yermack, 2017). Athey et al. (2016) and Pagnotta & Buraschi (2018) propose models of the valuation of digital currencies. Nevertheless, due to the high volatility, investors and researchers realized that Bitcoin fails to keep its promise that serves as a medium of exchange. Bitcoin is more regarded as a speculative asset rather than a method of payment for goods and services(Baur et al., 2018). This speculation drives volatility in the price of tokens, and it is becoming more a asset instead of a currency, which investors buy the token with fiat currency with an intention to resell it for profit, (Yermack, 2015; Glaser et al., 2014; Cheah, 2015).

Then, researchers turn their attention to the price relationships between different tokens. The relationship and interconnectedness of price between cryptocurrencies has been studied in multiple aspects, including connectedness and lead-lag relationships of different cryptocurrencies (e.g. Balcilar et al, 2017; Yarovaya and Zięba, 2022; Kristoufek, 2021; Moratis, 2021; Ji et al., 2019). The research on connectedness and lead-lag relationships across cryptocurrencies noted that Bitcoin is the centre of the crypto network (Stosic et al., 2018; Ji et al., 2019; Yi et al., 2018; Qiao et al., 2020; Hoang and Baur, 2021; Yarovaya and Zięba, 2022).

4. 2. 4. 2. Empirical review of Lead-lag effect

Our paper also makes contributions on literature stream of empirical studies on lead-lag relationships between different assets. Lead-lag relationships among different assets in traditional market have been widely documented in various trading frequencies. Studies focus on lead-lag relationship between stocks and corresponding index futures find that future prices lead the stock prices by up to 45 minutes (Zeckhauser and Niederhoffer, 1983; Kawaller et al., 1987). On the contrary, later research has revealed that lead-lag relationship between futures and stocks are bi-directional, but futures' leading is still stronger than the opposite way (Stoll and Whaley, 1990; Chiang and Fong, 2001). Hoffmann et al. (2013) observed lead-lag effects between equity and bond futures, with the DAX future leading the bond future by around one second. Further studies find that stock prices lead the prices of high yield bonds, indicating that the stock markets react to new information faster than bond markets (Tolikas, 2018).

On the other hand, the lead-lag relationships of different regions have attracted the attention of researchers, where the leading position of US market has been confirmed many times. Monteiro and Sebastião (2023) identify the leading role of US market by showing analyzing the lead-lag relationships of weekly returns of industries of six major markets. Alsayed and McGroarty (2014) find the S&P 500 leads FTSE 100 and DAX futures, which brings potential arbitrage opportunities.

Furthermore, the drivers of lead-lag effect has been studied widely, and previous research found it is strongly correlated with market microstructure. Zeckhauser and Niederhoffer (1983) examine the lead-lag relationships between stocks and futures, they provide evidence that lead-lag relationship is time-varying, and highly depends on market liquidity. Moreover, a majority of studies show that market characteristics, including volatility, size, and market frictions are the key drivers of lead-lag relationships.(Chordia et al., 2005; Kallberg and Pasquariello, 2008; Huth and Abergel, 2014).

Moreover, the lead-lag relationship in cryptocurrency market also received attention in recent times, where the leading position of Bitcoin in cryptocurrency market has been widely identified (Yarovaya and Zięba., 2022). Limited of these studies report bi-directional causality between Bitcoin and alt-coins (Sifat et al., 2019). These research on lead-lag relationship between different assets, including cryptocurrency, are conducted in various frequency level. Sifat et al. (2019) analyzed the lead-lag relationships between Bitcoin and Ethereum with hourly transaction prices, finding price of Bitcoin could significantly impact price of Ethereum. Yarovaya and Zięba (2022) investigate the lead-lag relationship of major cryptocurrencies with daily data and confirm the leading position of Bitcoin. Qureshi et al. (2020) demonstrate the origins of cryptocurrency market contagion is trivial in daily frequency scale. Li et al. (2022) capture the lead-lag relationship between Bitcoin and Altcoins due to the asynchronous impact factors between Bitcoin and related Altcoins can be used to predict Bitcoin price.

However, despite the lead-lag relationship in cryptocurrency market have been investigated multiple times in above literature (Sifat et al., 2019; Yarovaya and Zięba, 2022; Qureshi et al., 2020; Li et al., 2022), the dataset they used are limit to relative low and equally-spaced frequency, which are mainly daily-frequency and a few hourly dataset. We argue that in this era of high-frequency trading (O'Hara, 2015), analysis with these low frequency datasets might miss potential fast lead-lag relationship as the lead-lag effect could be sub-second, and these lead-lag relationship at low frequency could not provide useful information for actual trading. (Alsayed and McGroarty, 2014). We contribute to this strand of literature by utilizing high-frequency and tick-by-tick order book data to investigate the fast lead-lag relationship between cryptocurrencies. Contrary to existing literature, we identify the lag position of Bitcoin in high-frequency lead-lag relationship.

4. 2. 4. 3. High-frequency lead-lag effect

More recently, high-frequency lead-lag relationship raised researchers' interest in traditional equity asset. As the rapid increase of trades and trading speed in high-frequency trading era (O'Hara, 2015), the lead-lag effect is more likely to be short-living, even short than one second (Alsayed and McGroarty, 2014). Therefore, lead-lag relationships, during the era of high frequency trading, are more related to market microstructure information, such as limit order book activities. Nevertheless, using high-frequency and tick datasets from order books to analyze lead-lag effects is challenging since their changes occur at irregular time intervals. To address this problem, Hayashi and Yoshida (2005) propose the an estimator (HY-estimator) to calculate the correlation between two irregularly spaced time series with different lengths. This method makes it possible to examine high-frequency lead-lag relationship with tick-by-tick data. Furthermore, extended by Hoffmann et al. (2013), a more thorough comprehension has been offered, which could examine the strength of correlation as well as the timing of interaction.

The Hayashi-Yoshida (HY) method is designed specifically for tick-by-tick data, which is inherently irregular and asynchronous. Unlike methods relying on interpolation or discretization such as Granger Causality and Cross-Correlation Function (Granger, 1969; Lo & MacKinlay, 1990), HY estimation overcomes the major disadvantage of sparse sampling, the enormous data loss and the resulting inefficiency of the estimator. It avoids the loss of information caused by aggregating data into fixed intervals.

In empirical region, this HY-estimator has been widely applied in research to investigate lead-lag effect in a fast scale. Alsayed and McGroarty (2014) explore high-frequency lead-lag relationships in future market and find that S&P 500 future lead the FTSE 100 and DAX future about 300 ms. Huth and Abergel (2014) find that the price of CAC40 future lead its constituent shares. Moreover, they also find that liquid assets tend to be at a leading position. Dao et al. (2018) investigate lead-lag relationships between ETF and the corresponding index with HY method, they find that the index leads its replicating ETF from 10 to 30 milliseconds. Poutré et al. (2024) find lead-lag relationships of stocks in DAX market between three European exchanges, Chi-X, Xetra and BATS, they find Chi-X leads other two, but the lag lengths are less than 10 ms. Very limited research examines the fast cross-exchanges lead-lag relationship of in crypto market with HY-estimator. Schei and Rix-Nielsen (2019) investigate the lead-lag relationships of Bitcoin prices in different exchanges, finding that lag-length between exchanges ranges from 1 to 12 seconds. Another empirical study examine the fast lead-lag relationships between Bitcoin and Cardano, but without HY-estimators (Anderson, 2023), where they find Bitcoin is leading Cardano from 16 seconds to 128 seconds. We argue that these research on high frequency lead-lag relationships in cryptocurrency market is still at a preliminary stage, which did not get deserved attention. Furthermore, these rare but existing research mainly focus on Bitcoin, potentially overlooking leading altcoins such as Ethereum and Solana. We contribute to this strand of literature by extending past work with high-frequency data focusing on lead-lag relationship of Bitcoin, to more leading alt-coins, and identify factor that might affect the lag-length time between exchanges.

4. 3. Data

Our data set consists of the order book data of 4 most liquid cryptocurrencies, namely BTC, ETH, SOL and XRP from three leading centralized crypto exchanges, Kraken, Bitstamp and Bitfinex. Our data spans the period January 1, 2024 - January 31, 2024. Each token is monitored 24 hours per day as cryptocurrency is traded 24/7. In all, our dataset consists of updates of limit order book in excess of 100 million. According to Alsayed and McGroarty (2014), this high-frequency and tick-by-tick dataset with over 100 million data points is adequate, which allows us to capture the fast lead-lag relationship accurately.

The tick-by-tick snapshot of limit order book data includes timestamp, best ask price, best bid price, and the amount of tokens resting on the best ask and bid level. The time accuracy is at millisecond level. Our data is sourced from cryptotick.com, which is the only database provide pay-as-you-go data purchase, which means we can only buy the dataset we want without subscribing it. Table 4.1 provides an overview of the statistics of the data set.

As can be seen in Table 4.1, the order book datasets of cryptocurrencies in each exchange are fast updated with large amount of observations. The order book of most tokens in each exchange have over 10 million observations in sample period. The number of observations in Bitfinex are a bit less but still over 6 million. The average mid-quote price of same cryptocurrency in each exchange are close to each other and the maximum difference is about 1%, and the maximum price difference between exchanges is Solana. Specifically, the average mid-quote price of Solana in Kraken is 96.134 while it is 95.095 in Bitfinex, which is slightly over 1 %. In addition, Kraken has the lowest bid-ask spreads for all sampled tokens, which brings Kraken high liquidity and low transaction cost (Hagströmer, 2021). Similarly, Kraken has the deepest market depth for all cryptocurrency which is the number of tokens at the first level of the book (both the bid and ask), alongside with lowest bid-ask spread, Kraken has the highest liquidity among three sampled exchanges.

Table 4.1. Descriptive statistics of dataset.

Asset	Observations	Average mid quote price	Average bid-ask spread	Market depth
BTC in Kraken	13,180,874	43,182	1.510	9.052
BTC in Bitstamp	15,257,337	43,246	9.386	0.899
BTC in Bitfinex	7,549,786	43,103	5.448	1.297
ETH in Kraken	14,767,706	2,370.17	0.1574	95.22
ETH in Bitstamp	22,063,763	2,379.89	0.6691	9.076
ETH in Bitfinex	6,679,810	2,390.54	0.6855	8.2219
SOL in Kraken	17,471,787	96.134	0.0275	497.005
SOL in Bitstamp	18,388,840	95.839	0.0807	69.383
SOL in Bitfinex	22,268,958	95.095	0.0632	35.299
XRP in Kraken	10,684,583	0.5621	0.00013	18874.02
XRP in Bitstamp	13,693,620	0.5568	0.00016	13279.92
XRP in Bitfinex	6,554,990	0.5562	0.00026	7663.13

Table 4.1 presents the summary statistics of BTC/USD, ETH/USD, SOL/USD and XRP/USD quotes data in Kraken, Bitstamp and Bitfinex, collected from Cryptotick.com. Snapshot of limit order book data describe status of top of the order book, and it will be updated when the status changes. Average mid quote price and average bid-ask spread is in US dollar, market depth is the number of tokens at the first level of the book (both the bid and ask), which is in amount of token. Observation is the number of times that top of the order book has been updated. Sample period is from January 1, 2024 - January 31, 2024.

4. 4. Methodology

In practical financial markets, trading activities such as trades, order submissions, and deletions occur at irregular time intervals. Consequently, microstructure measures capturing aspects like price and liquidity are also recorded at non-synchronous timestamps. To accurately analyze lead-lag relationships between two such processes without introducing bias, we employ the correlation estimator proposed by Hayashi and Yoshida (2005). Through this method, we are able to deal with irregularly spaced time series with different lengths. In Hayashi and Yoshida (2005), they proposed a novel estimator of the covariance between two non-synchronous and irregular processes.

Specifically, let X_t and Y_t be two correlated processes such that:

$$dX_t = \mu^X X_t dt + \sigma^X X_t dW_t^X \tag{4.1}$$

$$dY_t = \mu^Y Y_t dt + \sigma^Y Y_t dW_t^Y \tag{4.2}$$

where W_t^X and W_t^Y are two variables that fit into Brownian motions. Assume that X_t and Y_t are sampled at discrete observation times $0 = t_0^X \leq t_1^X \leq \ldots \leq t_n^X = T^X$ and $0 = t_0^Y \leq t_1^Y \leq \ldots \leq t_n^Y = T^Y$, respectively, and X_t and Y_t are independent.

Then following Hayashi and Yoshida (2005), an unbiased estimate of the integrated correlation between X_t and Y_t is:

$$\hat{\rho} = \frac{\sum_{i,j} \Delta X(I_i^X) \Delta Y(I_j^Y) \mathbb{1}_{\{I_i^X \cap (I_j^Y)_l \neq \emptyset\}}}{\sqrt{\sum_i [\Delta X(I_i^X)]^2 \sum_j [\Delta Y(I_j^Y)]^2}}, \tag{4.3}$$

with $I_i^X = (t_{i-1}^X, t_i^X]$and $I_j^Y = (t_{j-1}^Y, t_j^Y]$ being all intervals between two observations in the process X_t and Y_t, respectively. The indicator function $\mathbb{1}_{\{I_i^X \cap I_j^Y \neq \emptyset\}}$ becomes 1 for all overlapping time intervals $I_i^X$and I_j^Y and 0 otherwise.

Equation 4.3 is the contemporaneous correlation. To estimate non-contemporaneous correlation at a given lag l, the estimator was extended by Hoffmann et al. (2013). The principle of this extension is to shift the observation times of Y_t by a certain lag length l, then the integrated correlation between shifted process Y_{t+l} and X_t is :

$$\hat{\rho}(l) = \frac{\sum_{i,j} \Delta X(I_i^X) \Delta Y(I_j^Y) \mathbb{1}_{\{I_i^X \cap (I_j^Y)_l \neq \emptyset\}}}{\sqrt{\sum_i [\Delta X(I_i^X)]^2 \sum_j [\Delta Y(I_j^Y)]^2}}, \tag{4.4}$$

with $(I_j^Y)_l = (t_{j-1}^Y + l, t_j^Y + l]$. The $l*$ that maximizes the HY-curve in absolute terms is denoted as lead - lag value (or lead-lag time) (Hoffmann et al., 2013) and indicates whether Y_t leads ($l* > 0$) or lags ($l* < 0$) X_t.

Finally, Huth and Abergel (2013) define the notion of a lead-lag ratio (henceforth LLR) which we also employ to determine the direction of lead-lag effects. It s defined as follows:

$$LLR = \frac{\sum_{l=l}^{L} \hat{\rho}^2(+l)}{\sum_{l=l}^{L} \hat{\rho}^2(-l)}, \tag{4.5}$$

The quantity $\hat{\rho}(l)$ provides the correlation coefficient between X and Y at lag length l, where a positive l indicates that Y leads X. Similarly, $\hat{\rho}(-l)$ represents the correlation coefficient when Y lags X by l units of time. The numerator of LLR is the sum of squared correlation coefficients for all instances where Y leads X, while the denominator is the sum of squared correlation coefficients when Y lags X. With this in mind, the purpose of LLR is to quantify the relative strength of the lead-lag relationship in both directions. An LLR greater than 1 suggests that Y more strongly leads X than vice versa, whereas an LLR less than 1 implies that X predominantly leads Y. Prior literature establishes the LLR because lead-lag relationships are broadly bi-directional (Wang and Wang, 2001), and the LLR provides a means to quantify their relative strength in each direction. The LLR helps decouple bi-directional lead-lag relationships by quantifying their relative strengths and direction. In one word, LLR effectively captures both the strength and direction of the lead-lag relationship between two asynchronously recorded time series.

4. 5. Empirical results

4. 5. 1. The Lead-Lag Relationship Between Cryptocurrencies

There are 31 trading days in our sample period. For each day, to investigate the lead-lag relationship of different cryptocurrencies in same exchange, we estimate the entire HY cross-correlation curves between 4 leading cryptocurrencies in each exchange on each trading day, then we average the curves over all days. To investigate the lead-lag relationship of different exchanges in terms of same cryptocurrency, we estimate the entire HY cross-correlation curve of difference exchanges in terms of same cryptocurrency over all days. We therefore ultimately obtain a single HY curve for each pair. This step helps quantify the relative strength and direction of the lead-lag relationships for different cryptocurrencies in same exchange. If the curve is asymmetric or the maximum correlation does not show at 0 lag length, it suggests lead-lag relationships between these two time series. For each pair, we measure leads and lags of mid-quote returns on a horizon of −5 to 5 seconds, with 50 millisecond increments. We justify this horizon by the fact that cross-correlations across all pairs might diminish substantially within a second (Alsayed and McGroarty, 2014).

The results of the lead-lag relationship of different cryptocurrencies in same exchange are presented in Figure 4.1 and Figure 4.2. Figure 4.1 and Figure 4.2 presents the evidence of lead-lag relationships of different tokens in Kraken and Bitfinex, respectively while no significant lead-lag relationship between cryptocurrencies is detected in Bitstamp. The results show that the lead-lag relationships of 4 cryptocurrencies vary in different exchanges. But largely, Solana and XRP are at leading positions while Bitcoin is at a lagging position. Due to space limit, only significant lead-lag relationships are displayed.

Figure 4.1. Lead-Lag Relationships in Kraken.

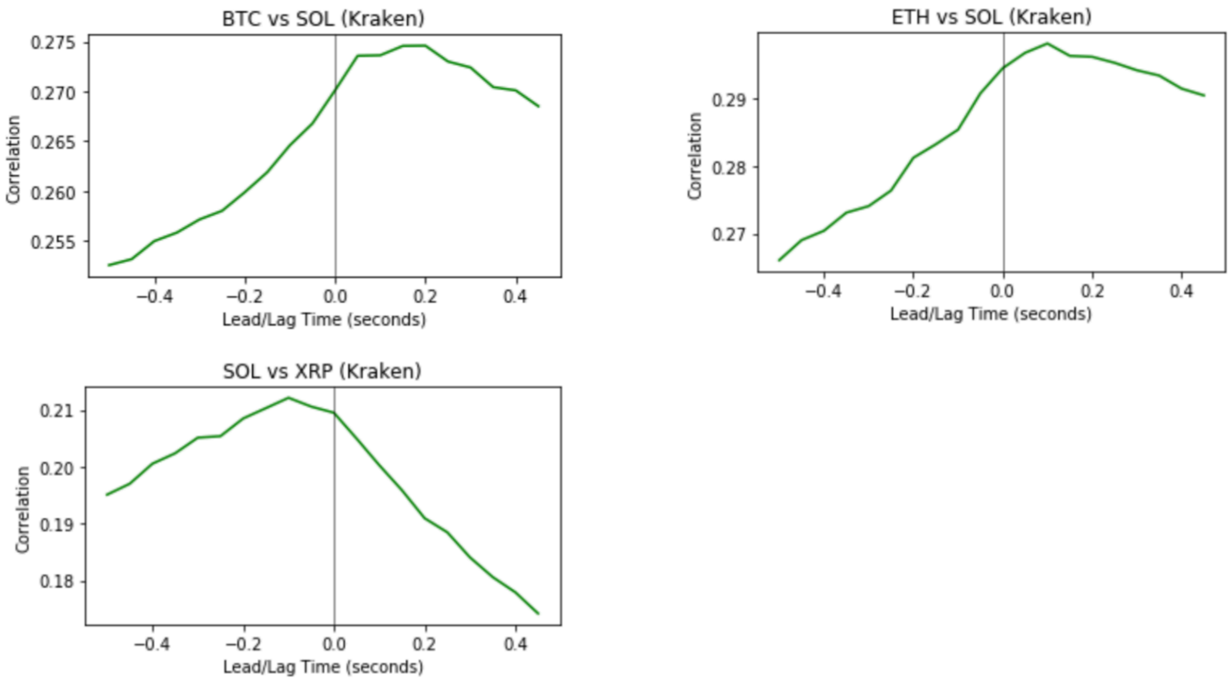


Figure 4.1 displays the significant lead-lag relationships among 4 tokens in Kraken. The HY curves plotted for BTC/SOL, ETH/SOL and SOL/XRP in Kraken, other pairs have no significant lead/lag relationship. To be more clear, these diagrams zoom in on lag lengths l □ [−0.5, 0.5] seconds with 50 ms increments. $l > 0$ indicates the cryptocurrency whose name appears first in the title lags, and vice versa. For example, in BTC/SOL, l associated with maximum correlation is great than 0, indicating BTC lags and SOL leads.

Specifically, Figure 4.1 presents the significant lead-lag relationships of 4 tokens in Kraken. It shows SOL is at a leading position in Kraken, which leads another three tokens, and there is no significant lead-lag relationship existing among other 3 tokens. Solana leads Bitcoin about 150 ms, and leads both Ethereum and XRP about 100 ms. Furthermore, Figure 4.2 presents the significant lead-lag relationships between 4 tokens in Bitfinex. It indicates that

Bitcoin is at a lagging position in Bitfinex since other three tokens are all leading Bitcoin, and XRP leads Ethereum as well. Specifically, Bitcoin lags Ethereum, Solana and XRP about 50ms, 50ms and 100 ms, respectively, while Ethereum lags XRP about 50ms. No significant lead-lag relationship is detected between ETH and SOL or between SOL and XRP in Bitfinex. There is no significant lead-lag relationship among these four cryptocurrencies in Bitstamp.

Figure 4.2. Significant Lead-Lag Relationships in Bitfinex.

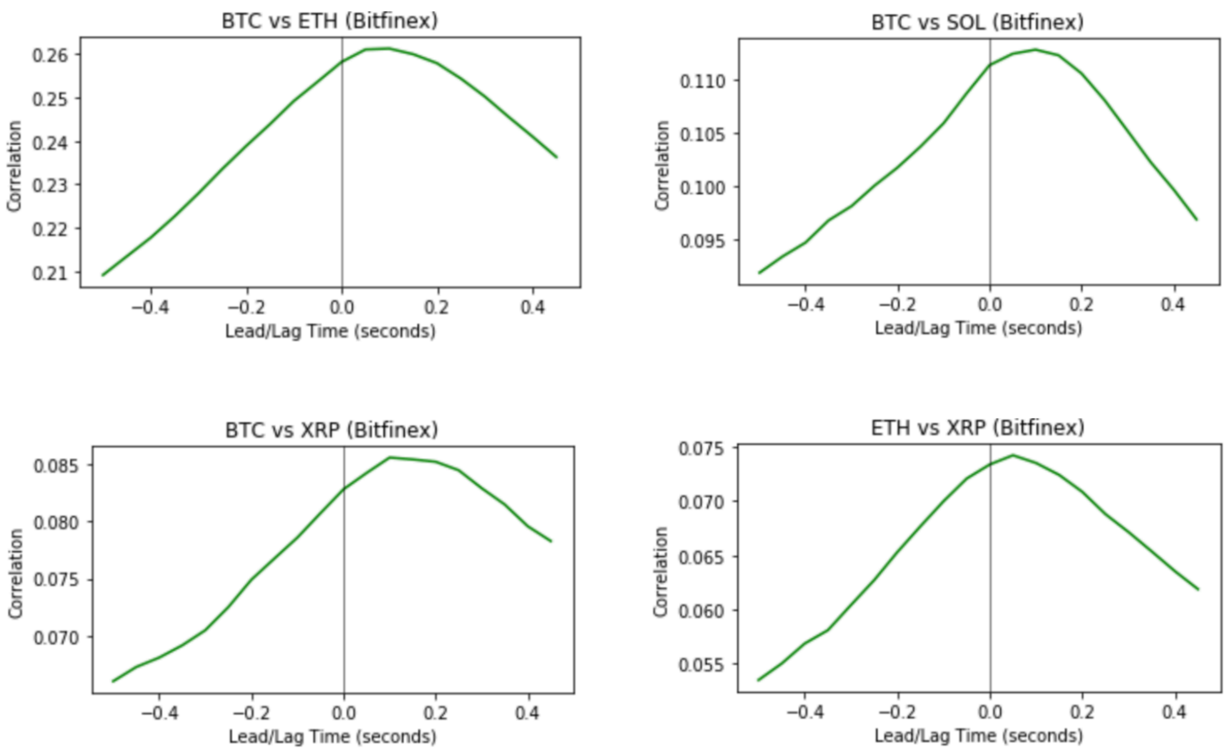


Figure 4.2 displays the significant lead-lag relationships among 4 tokens in Bitfinex. The HY curves plotted for BTC/ETH, BTC/SOL, BTC/XRP and ETH/XRP in Bitfinex, other pairs have no significant lead/lag relationship. To be more clear, these diagrams zoom in on lag lengths $l \in [-0.5, 0.5]$ seconds with 50 ms increments. $l > 0$ indicates the cryptocurrency whose name appears first in the title lags, and vice versa. For example, in BTC/ETH, l associated with maximum correlation is great than 0, indicating BTC lags and ETH leads.

The results indicate that price discovery is not simultaneous across assets, even in highly liquid digital markets. Instead, information and order flow are first incorporated into certain assets before propagating to others. The result that Bitcoin is at the lagging position suggests that previous findings about Bitcoin's dominance position in the crypto ecosystem may not hold at high-frequency domain (Sifat et al.,2019; Yarovaya and Zięba, 2022). In market microstructure terms, this pattern reflects differences in trading speed, liquidity provision, and information diffusion across assets (Stein, 1999; Chord et al., 2008; Theissen, 2016;). Given the benchmark position of market cap and sentiment of Bitcoin, one possible explanation is that its deeper limit order book and larger retail participation may cause slightly slower adjustment to new information, and tend to absorb price impact (Benos et al., 2017; Menkveld & Zoican, 2017). We will further analyze this in detail in part 4.5.3.

This results are consistent with theoretical work in price discovery (Hasbrouck, 1995), which emphasizes that leadership in information incorporation depends on combination of liquidity and trading activity, not only on size or market dominance. The shift of positions of Bitcoin in lead-lag relationships underscores the importance of considering various time scale of analysis, especially high-frequency when assessing leadership in price discovery.

4. 5. 2. The Lead-Lag Relationship Between Exchanges

Then we turn our attention to the lead-lag relationships of exchanges in terms of same tokens. More specifically, we investigate the lead-lag relationships between same cryptocurrency in different exchanges. The results of lead-lag relationship between crypto exchanges in terms of each token are presented in Table 4.2. Overall, Bitstamp and Kraken are at the leading positions while Bitfinex is at the lagging position. However, these lead-lag relationships vary for different tokens.

As can be seen in Table 4.2, it shows Bitstamp is at the leading position for most tokens while Bitfinex is at a lagging position for all tokens, where Bitstamp leads Kraken both in Bitcoin and Ethereum for 50ms, and leads Bitfinex in all four tokens for 50ms to 150 ms. Bitfinex is largely at a lagging position as it lags Kraken in Bitcoin, SOL and XRP for 50 ms to 150ms, and lags Bitstamp in all four tokens. Additionally, we note that the lead-lag relationships of exchanges vary in terms of different tokens, which indicates exchange at a leading position for one token might be at a lagging position for another. For example, Kraken lags Bitstamp in Bitcoin and Ethereum, but it leads Bitstamp in Solana. Specifically, for Bitcoin, Bitstamp is at the leading position where the price in Bitstamp leads that in Kraken about 50 ms, and Kraken as well as Bitstamp both lead Bitfinex about 150 ms. For mid price of Ethereum, Bistamp is also at a leading position where Kraken lags Bitstamp for about 50 ms, while Bitfinex leads Kraken for about 50 ms, and Bitstamp leads Bitfinex about 50 ms. For mid price of Solana, Kraken is at the leading position, where Kraken leads Bitstamp and Bitfinex for about 50 ms and 100 ms, respectively, and Bitstamp leads Bitfinex for about 150 ms. For XRP, Bitfinex is at the lagging position, where there is no significant lead-lag relationship between Kraken and Bitstamp, but Kraken and Bitfinex both lead Bitfinex about 50 ms.

Table 4.2. Lead-Lag relationship between exchanges in terms of different tokens.

	BTC	ETH	SOL	XRP
Kraken lead Bitstamp	-50ms	-50ms	50ms	0
Kraken lead Bitfinex	150ms	-50ms	150ms	50ms
Bitstamp lead Bitfinex	150ms	50ms	100ms	50ms

Table 4.2 presents the lead-lag relationships between centralized exchanges in terms of 4 tokens. Each column represents lead-lag relationship among three exchanges in terms of one token. For example, the second column displays the result of lead-lag relationship of BTC in different exchanges. If length time is positive, then it is the direction shown in the first column of the row, otherwise it is the opposite way.

The presence of sub-second lead-lag relationships across the same cryptocurrency on different exchanges suggests that price discovery is at different speed and fragmented across trading venues. The results of lead-lag relationships between exchanges show that Bitfinex is always at lagging positions for all sampled cryptocurrencies, which has the lowest liquidity and highest trading fee among three exchanges[18]. Our results present that crypto exchange with low liquidity and high transaction cost is more likely to be at the lag position on price discovery. Bitfinex's relatively low liquidity means that its order book are thinner and less capable of absorbing shocks quickly, and its higher trading fees discourage the participation of arbitrageurs and professional liquidity providers who typically adjust prices across venues. Consequently, the reduced arbitrage activity and slow order flow response positions Bitfinex as a follower in the price discovery process. These findings are consistent with previous theoretical work on how market microstructure impact the speed of information diffusion and price discovery, which highlight that markets with lower liquidity and higher transaction costs tend to attract fewer informed or high-frequency traders,

[18] https://www.kraken.com/features/fee-schedule; https://www.bitstamp.net/fee-schedule/; https://www.bitfinex.com/fees/

leading to slower adjustment to incoming information (Amihud and Mendelson, 1986; Grossman and Miller, 1988; Hasbrouck, 1995).

4. 5. 3. Mid-price stickiness and order book resilience

So far, we have identified that BTC is at the lagging position in high-frequency mid-price lead-lag relationship with order book data. In order to find possible explanations of BTC's lagging position, we investigate the mid-price stickiness and market depth of each tokens.

In high-frequency financial markets, mid-price dynamics are broadly influenced by the structure order book, particularly the market depth at the best bid and ask prices. According to previous theoretical works in market microstructure (O'Hara, 1995; Bouchaud et al., 2009), the market with deep order book is more tending to effectively absorb market shocks such as incoming market orders, instead of reacting to them, reducing the frequency of mid-price updates, which is known as market stickiness. In this context, assets with greater depth at the top of the book tend to exhibit less responsive mid-price dynamics, which potentially makes them lag in high frequency mid-price lead-lag relationship. To investigate if mid-price stickiness and market depth is one factor that could the lead-lag position of each cryptocurrencies, we measure the mid-price updated frequency and market-depth of each token. This measure could reflect the changes of mid-price, contributing to a deeper understanding of lead-lag relationships and the drivers of price discovery across crypto-assets (Hasbrouck, 1995).

Using a value-based market depth that facilitates cross-asset comparison, we measure dollar market depth as the sum of quoted quantities at the best bid and ask and weighted by the prevailing mid-price at a one-minute frequency and averaging across all minutes of a trading day over sample period. According to Benos et al. (2017) and Menkveld & Zoican (2017), the use of dollar-depth not only enables us to compare market depth across assets, but also captures the absolute volume available at the top of the order book and reflects the market's ability to absorb incoming orders without large price adjustments. Simultaneously, following a growing body of high-frequency market microstructure research (i.e. Bouchaud et al., 2009), we quantify the frequency of mid-price updates as the number of distinct changes in the mid-price per minute, and averaging across all minutes of a trading day over sample period. The results of market depth and frequency of mid-price updates of sampled cryptocurrencies in Kraken are shown in Fig 4.3 and Fig 4.4.

Fig 4.3. The intraday dollar-depth of cryptocurrencies in Kraken.

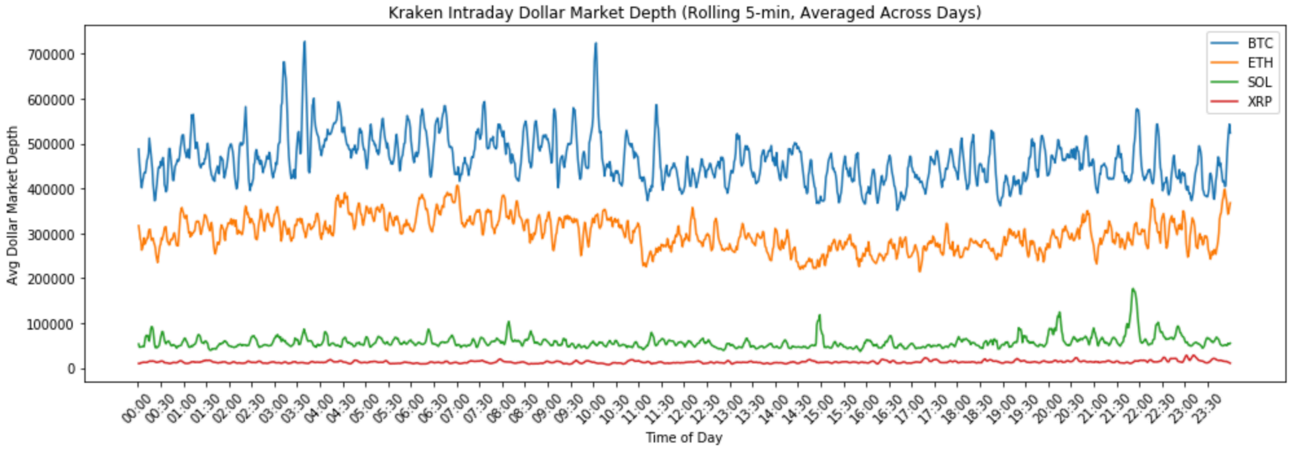


Figure 4.3 shows the dollar market depth of sample cryptocurrencies in exchange Kraken. We calculate this intraday market depth by calculating the one-minute dollar depth with five-minutes rolling window and averaging across all minutes of a trading day over sample period.

Fig 4.4. The intraday mid-price updates frequency of cryptocurrencies in Kraken.

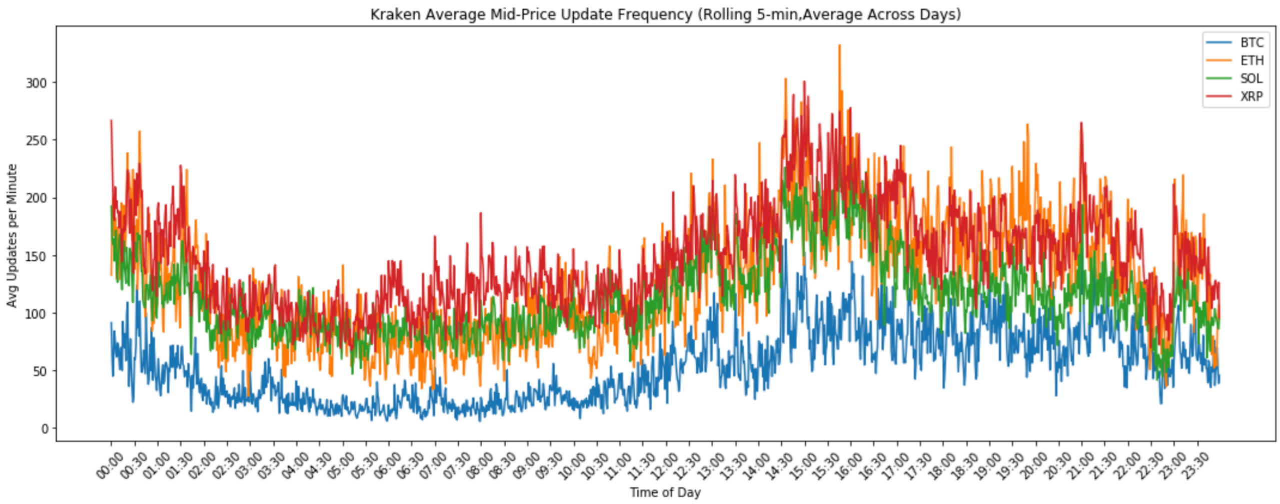


Figure 4.4 shows Mid-price updates frequency per minute of a day in sample period of each cryptocurrencies in exchange Kraken. We calculate this intraday mid-price updates frequency by calculating the numbers of mid-price updates in each minute and averaging across all minutes of a trading day over sample period.

Figure 4.3 shows the dollar market depth of sample cryptocurrencies in Kraken. As can be seen in Figure 4.3, these four sampled cryptocurrencies have very different dollar-depth in

Kraken, where Bitcoin has the deepest market depth, ETH has the second deepest market depth, and SOL and XRP has the third and last deepest market depth among four sample cryptocurrencies. The results seem to indicate that deep market depth is correlated with lagging position in mid-price high frequency lead-lag relationship. Particularly, in part 4.5.1, results in figure 4.1 show that Bitcoin and Ethereum is lagging behind SOL and XRP while XRP leads SOL. The results suggest that cryptocurrencies with deeper market depth are likely to be laggers in the lead-lag relationships of mid-price.

Then we turn our attention to the frequency of mid-price updates. The results of mid-price updates frequency of each cryptocurrency in Kraken are shown in Figure 4.4. As can be seen, XRP has the highest updates frequency and SOL, Ethereum and Bitcoin have the second, third and least mid-price updates frequency respectively. It shows that the mid-price updates frequencies of cryptocurrencies match their positions in mid-price lead-lag relationships, where cryptocurrencies with higher mid-price updates frequencies tend to be at the leading positions.

Finally, we investigated the mid-price response to market shock. Specifically, we calculate the percentage change in the mid-price of each cryptocurrency at intervals from 0.1 seconds to 1 second, with a 0.1-second gap. The mid-price changes percentage of cryptocurrencies in Kraken are shown in figure 4.5. As can be seen, cryptocurrencies with deep market depth and lower mid-price update frequency have smaller mis-price response to shocks. Specifically, Bitcoin has the smallest mid-price changes to shocks while XRP has the largest mid-price changes. These price response to shocks suggest that cryptocurrencies have different order book resilience to market shock, where cryptocurrencies have deep market depth and lower mid-price update have higher ability to absorb market shocks, and thus have relative stable mid-price. Comparing these results to the lead-lag relationships of cryptocurrencies in Kraken which are shown in figure 4.1, we note that cryptocurrencies with deep market depth and high mid-price update frequency tend to have small price response to market shock, such as Bitcoin and Ethereum, which are at the lagging positions. Cryptocurrencies with shallow market depth and high mid-price update frequency have large price response to market shock, such as SOL and XRP, which are at the lagging positions.

The dollar market depth and frequency of mid-price updates of sample cryptocurrencies in

Bitfinex are shown in Appendix C.1, C.2 and C.3, which show similar results as Figure 4.3, Figure 4.4 and Figure 4.5.

Fig 4.5. The mid-price change percentage of cryptocurrencies in Kraken.

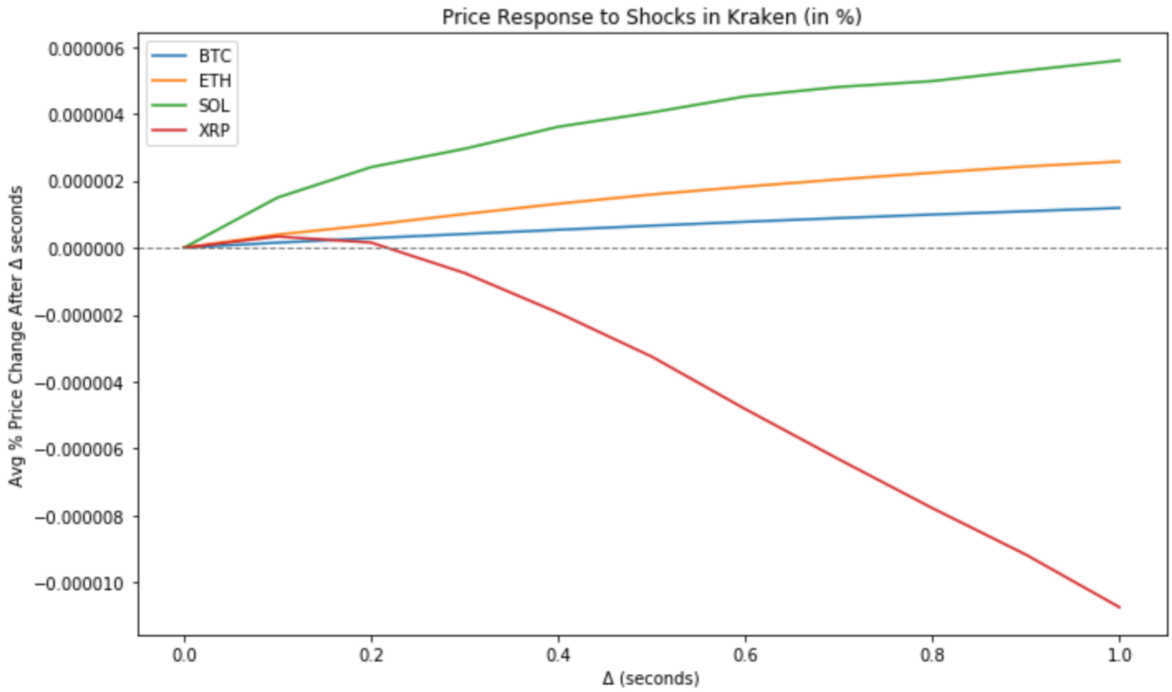


Figure 4.5 shows the average mid-price change after Δ seconds of sample cryptocurrencies in exchange Kraken. We calculate the percentage of changes of mid-price from 0.1 second to 1second interval, and then average the results to plot the curves of figure 4.5.

Taken together, the results presented in Figures 4.3, 4.4 and 4.5 provide a coherent explanation for the high-frequency lead-lag relationships observed among the sampled cryptocurrencies in same exchanges. Cryptocurrencies with deeper dollar market depth exhibit higher order book resilience, which is demonstrated as lower mid-price updates frequency and smaller response to market shock (Kempf et al., 2009). These cryptocurrencies, such as Bitcoin and Ethereum, are more likely to occupy lagging positions in high-frequency price discovery process. In contrast, those with shallower depth, such as XRP and SOL, demonstrate more frequent mid-price updates and tend to be at the leading positions in the lead-lag relationships. These findings suggest that liquidity characteristics at the top of the order book, particularly depth and price update behavior, might be important microstructure drivers of high-frequency lead-lag relationships in crypto markets.

The observed results of mid-price update frequency and response as well as market depth and lead-lag relationship indicates that market microstructure theory are suitable in cryptocurrency markets, especially in high frequency lead-lag relationships. Specifically, assets that exhibit more frequent mid-price changes are generally more responsive to new order flow and information arrivals, suggesting that they play a more active role in the price discovery process (Menkveld and Zoican, 2017). On the contrary, assets with deeper market depth tend to absorb market shocks such as order flow, instead of react to them (Degryse et al., 2005). Particularly, prices in limit order book responses to order flow shocks gradually instead of instantaneously, which depends on market depth. Mid-price is more likely to change frequently when market depth is thin (Bouchaud et al., 2009). In contrast, assets with deeper market depth tend to absorb more order flow without immediate price revisions, resulting in fewer mid-price updates—a phenomenon broadly referred to as mid-price stickiness. This mid-price stickiness reflects the market's capacity to mitigate transient shocks and delay price adjustments, thereby contributing to a lagging position in high-frequency lead-lag relationships (Hasbrouck, 1995; Menkveld and Zoican, 2017).

4. 5. 4. The Intraday Profile of Lead-Lag Relationships

It is a commonsense that financial markets demonstrate intraday patterns, such as U-shaped volatility (Alsayed and McGroarty, 2014). So far, we have established an overall high-frequency lead-lag picture across three crypto exchanges and four cryptocurrencies. Now we turn our attention to the intraday pattern of these relationships. Following Alsayed and McGroarty (2014), we split each day into 24 hourly intervals, spanning 00:00 - 23:59 UTC as cryptocurrency is 24/7 traded on these centralized exchanges. In this part, we investigate the lead-lag relationships between Kraken and Bitstamp in terms of each sample cryptocurrency to analyze the intraday patterns. For each interval, we measure the maximum correlation and lag length which maximizes the correlation for each pair and on each day. Then we average these results over the number of days. Ultimately, we obtain four 24-point curves: one for each pair. The results of Bitcoin and Ethereum are shown in Figure 4.6 and results of SOL and XRP are shown in appendix C.4.

Figure 4.6 provides clear evidence of intraday seasonality of lead-lag relationships between Kraken and Bitstamp in terms of Bitcoin and Ethereum. It turns out when US stock market is opening, the lag length of two exchanges is shorter and the max correlation is smaller. The the announcement of macroeconomic news at 13:30 UTC, the US stock market open at 14:30 UTC, and the close of US stock markets at 21:00 UTC.

In Figure 4.6, the largely positive lag length of Kraken suggest that Bitstamp is leading Kraken in both Bitcoin and Ethereum at most time, the max correlation fluctuates between 0.3 and 0.45. Moreover, the maximum correlation generally decreases throughout the day, and bounces back at 21:30 UTC to 22:30 UTC. This implies that the pairwise causal link between the leading and lagging exchanges varies throughout the day. The maximum correlation of Bitcoin and Ethereum are at the lowest level throughout the day from 14:30 UTC to 21:00 UTC, which exactly matched the opening period of US stock market, and then it increases sharply since US stock market closed. In addition, the lag length shows a intraday seasonality as well. Kraken lags Bitstamp in both Bitcoin and Ethereum. The lag length remains largely range-bound, which volatiles between 0 and 150 ms. For Bitcoin, the lag length is lower at the interval of 6:00 UTC to 8:00 UTC and interval of 16:00 to 18:00 UTC. For Ethereum, the lag length are relative low from 14:30 UTC to 21:00 UTC, which almost cover the open time of US stock market. The intraday lead-lag relationships between Kraken and Bitstamp in terms of SOL and XRP are shown in Appendix C.4, which displays similar results as Figure 4.6.

The results largely show that the opening of the US stock market reduces the lag length and maximum correlation between Kraken and Bitstamp, while the closing of the US stock market intensifies them. This indicates that the information transmission between crypto exchanges is more dependent on the intensity of activity of US market. During the trading hours of the US financial market, when both markets and investors, especially institutional investors, are active, information transmission is faster, resulting in smaller price lags. Our findings are consistent with previous studies on lead-lag relationship in traditional market that lead-lag effect is correlated with intensity of market activity (Chordia et al., 2011; Rakotomalala and Cao, 2019). This might be due to higher market liquidity and lower transaction cost (Kyle, 1985; Amihud and Mendelson, 1986), more arbitrage tradings (Hasbrouck, 1995) and more high frequency tradings (Hasbrouck and Saar, 2013). Our results prove that previous findings on drivers of lead-lag effect could be applied in cryptocurrency market.

Figure 4.6. Intraday Lead-Lag relationship of Kraken and Bitstamp in Bitcoin and Ethereum.

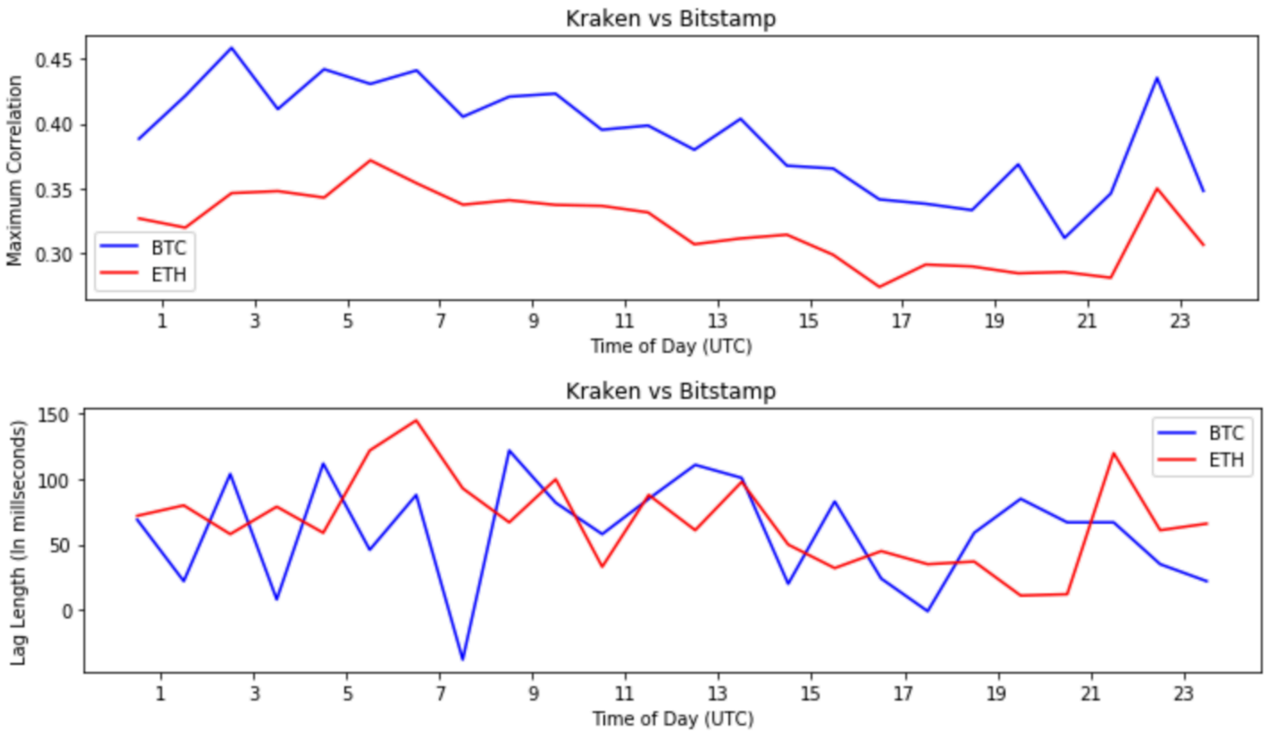


Figure 4.6. Lead-Lag intraday pattern. Intraday patterns in the Maximum correlation and Lag length of Kraken and Bitstamp in Bitcoin and Ethereum. The blue and red curves denote Bitcoin and Ethereum, respectively. The Lag Length denotes the lag time of Kraken, it indicates Kraken lagging Bitstamp if it is positive and Kraken leading Bitstamp if it is negative. Times on the horizontal axes refer to the previous one-hour interval (e.g. 9:30 refers to the 09:00-10:00 interval).

4. 6. Discussions

This study investigates the fast lead-lag effect in cryptocurrency markets in this study. Specifically, we examine the lead-lag relationships between crypto exchanges in terms of same tokens, and that between different tokens in same exchanges. In this high frequency trading period (O'hara, 2015), lead-lag relationship is super fast and might be more likely to occur in the sub-second region and to be more short-living (Alsayed and McGroarty, 2014; Huth and Abergel, 2014). Therefore, prior research on lead-lag effect in crypto market using fixed sampling frequencies of weekly, daily or intraday basis could not provide practical information for actual trading or arbitrage (Alsayed and McGroarty, 2014). We apply the method proposed and extended by Hayashi & Yoshida (2005) and Hoffmann et al. (2013). This method allows us to process the irregular tick-by-tick dataset from limit order book to examine the high-frequency lead-lag relationship in cryptocurrency market.

These strong lead-lag effects we documented indicate that the information diffusion is not instantaneous or synchronous in cryptocurrency market. Even though the trading in cryptocurrency market is high frequent and super fast[19] (Aleti & Mizrach, 2021;), the information is still not instantly spread to all exchanges and tokens.These results challenge the implication of the Efficient Market Hypothesis (EMH) that prices adjust so quickly to new information that opportunities for excess returns do not exist, due to the assumption that information transmission is instantaneous, complete, and frictionless. Our findings are supportive to Adaptive Market Hypothesis (AMH) and the theory proposed by Grossman and Stiglitz (1976, 1980), which suggest that information transmission in financial markets is dynamic, costly, and influenced by market conditions and participant behavior. As a result, prices may not always immediately reflect all available information.

Contrary to previous studies on lead-lag relationships in crypto markets (Yarovaya and Zięba, 2022), we confirm the lagging positions of Bitcoin and Ethreum in high-frequency lead-lag relationships. Our further analysis on limit order book shows that these lag positions of Bitcoin and Ethereum might correlated with market depth. Our study shows that Bitcoin and Ethereum have higher dollar-depth than other tokens, bringing higher order book resilience to market shock, which is reflected by lower mid-price update frequencies and smaller response to market shock. These low mid-price update frequencies and smaller response to market shock might make Bitcoin and Ethereum look react slower to new information. Our findings are consistent with previous works focus on limit order book where they find assets with deeper market depth have the ability to absorb market shocks and keep mid-prices stable. (Menkveld and Zoican, 2017; Degryse et al., 2005).

Moreover, our results prove that the lead-lag effect is correlated with market condition and market microstructure factors including bid-ask spread and transaction cost. In detail, in terms of same tokens, we found Bitfinex is always at lagging positions for all four sample cryptocurrencies. One possible reason is that among these three centralized crypto exchanges, Bitfinex has widest bid-ask spread and highest trading fee. Our results indicate that crypto exchange with low liquidity and high transaction cost is usually at the lag position on price discovery. These findings provide empirical evidence to support previous theoretical work which claim that high trading cost would slow the information diffusion

[19] https://blog.kraken.com/crypto-education/performance-at-kraken

and thus have slower price discovery (Amihud and Mendelson, 1986; Hasbrouck, 1995; Grossman and Miller, 1988).

In addition, we detected a strong intraday seasonality of lead-lag relationship between exchanges in terms of same cryptocurrencies. Specifically, during the opening time of US stock market, the lead-lag relationship between exchanges diminished. Consistent with previous papers on price discovery (e.g. Chordia et al., 2011; Alsayed and McGroarty, 2014), our results prove that information spreads faster when markets are more active. This is possible due to the higher liquidity and trading volume (Kyle, 1985; Biais et al.,1995), more intensive arbitrage (Hasbrouck, 1995) and more algorithm trading from institutional traders (Hasbrouck and Saar, 2013) during the day time and opening time of US financial market.

Overall, our results fit into the implications of AMH (Lo. 2004) and information model (Grossman and Stiglitz, 1976, 1980) that information is not transmitted instantaneously, but rather exhibit brief delays. Therefore, the speed to act on new information varies for different market participants and thus they have different price discovery speed, which introduce lead-lag effect to the market. And the lead-lag effect is diminished when market activity is intensified during the opening time of US stock market. Our findings are consistent with AMH and price discovery theory in previous work (e.g. Hong & Stein, 1999; Hasbrouck, 1995; Lo & MacKinlay, 1990; Chordia & Swaminathan, 2000; Lo, 2004), showing that these theories fit into emerging markets such as cryptocurrency market.

4. 7. Conclusions

This paper complements previous work by examining fast lead-lag relationships of mid-quote price in the important but overlooked market setting of cryptocurrency. We document clear evidence of sub-second lead-lag patterns across 4 top cryptocurrencies, Bitcoin, Ethereum, Solana and XRP, in three top centralized exchanges, Kraken, Bitstamp and Bitfinex. Using milliseconds tick-by-tick order book data, we analyze high frequency lead-lag relationships of different tokens in same exchange, and same token in different exchanges. Our results suggest that the diffusion of information across these exchanges and tokens is not instantaneous. And our further analysis indicates that the lead-lag positions of cryptocurrencies are correlated with order book depth and resilience.

Moreover, the lead-lag relationship shows a strong seasonality in intraday patterns. During the opening time of US equity market (13:30 UTC to 21:00 UTC), the maximum correlation and lag length are at the lowest level throughout a day. This indicates that the diffusion of information tends to be faster when market is active.

The data we employ consists of the four most highly liquid cryptocurrencies in three top centralized exchanges, with no capital controls and no restrictions to cross-border arbitrage in cryptocurrency market setting. Based on this, we suggest that the results obtained in this paper are generalizable to other global markets. Our dataset contains over 100 million data points throughout the sample period, providing us enough sample to investigate the lead-lag relationship in cryptocurrency market with a more granule and faster scale. Furthermore, we highlight the importance of utilizing high-frequency data, based on compelling evidence that most of the mechanisms of price adjustment and order match in cryptocurrency market operate deep into the sub-second domain.

Our results have important implications to cryptocurrency investors and centralized exchanges. The high-frequency lead-lag effects might provide extra information on forecasting possibility of cryptocurrency price changes, which could help investor improve arbitrage strategy. For exchanges, our results also bring new sights to them on how to reduce lag-length seasonality and speed up the information transmission.

Overall, we provide new insights on non-contemporaneous cross-asset correlations in emerging and fast cryptocurrency market. We find evidence of high-frequency lead-lag effects of cryptocurrency price. Bitcoin and Ethereum, the leading cryptocurrencies in previous analysis with lower frequent dataset, lost their leading positions in this high-frequency scale. The lead-lag relationships between different cryptocurrencies vary over time, which display a strong seasonality in intraday patterns. Future work could focus on exploring the arbitrage limits and opportunities by exploiting the high-frequency lead-lag relationships. This would facilitate relieve the disequilibria of information diffusion in cryptocurrency market cross centralized exchanges and tokens.

Chapter 5

Conclusions

5.1. Main findings and implications

In conclusion, this thesis provides a comprehensive analysis of the volatility transmission mechanisms from external markets to stablecoin markets, as well as the mispricings of stablecoins that give rise to arbitrage opportunities. It investigates the factors associated with stablecoins volatility and price deviations. Additionally, this study examines rapid lead-lag relationships across cryptocurrencies and crypto exchanges using high-frequency data.

The primary objective of this thesis is to understand the dynamic linkage between fiat-collateralized stablecoins and various related markets and influential factors, and to determine how these different factors can majorly contribute to the volatility and price deviations of stablecoins over time. A major outcome of this thesis is that the volatility spillovers from related external markets to stablecoins markets have been identify, which are the drivers of stablecoins excess volatility, while microstructure factors and asynchronous price adjustments of crypto exchanges contributes to cross-exchanges mispricings of stablecoins. Furthermore, we also document strong, sub-second lead-lag effects among cryptocurrencies across and within exchanges, expanding the literature on high-frequency lead-lag relationships in cryptocurrency market.

Chapter Two examines potential drivers of stablecoin volatility using linear regression and volatility spillovers approach proposed by Diebold and Yilmaz (2009, 2012, 2015) combined with Time-varying Parameter VAR model. Our results indicate shocks from related markets, including traditional cryptocurrencies markets, major equity and currency markets, could transmit to stablecoins markets. This chapter provides important implications to crypto traders that the spillover effects from external markets to stablecoins should be considered when they build their trading strategy relying on the stability of stablecoins as strong spillover effects might bring potential risks to these strategies. Also, by leveraging evidence of strong spillover effects from external markets to stablecoins, investors can time their trades of stablecoins more effectively to avoid uncertainties in transaction costs.

Chapter Three identifies massive frequent and quick-removed mispricings within stablecoin secondary markets across centralized exchanges, demonstrating profitable arbitrage opportunities even after accounting for transaction costs. In addition, by analyzing the market characteristics that prevail during mispricings, we find the microstructure factors — such as bid-ask spreads, market depth, order imbalance, and return standard deviation, play important roles in creating mispricings that lead to arbitrage opportunities. Further impulse response function analysis suggests that asynchronous price adjustments across exchanges contribute to the observed mispricings. This chapter provides valuable implications for arbitrageurs, stablecoin managers and cryptocurrency exchanges. For arbitrageurs, they can exploit this new arbitrage route to avoid high trading cost and threshold of primary market, and further remove smaller price deviations of stablecoins. For stablecoin managers, the findings highlight the vulnerability of stablecoin price stability to large one-sided orders and liquidity shortages, suggesting a need to strengthen stability mechanisms. For crypto exchanges, our results indicate that improving the speed of price discovery might be a useful way to reduce stablecoins mispricings and enhance market efficiency.

Chapter Four complements previous work by examining high-frequency lead-lag relationships in the important but overlooked market of cryptocurrency. Using milliseconds tick datasets of order book, this chapter analyzes lead-lag patterns between different tokens within the same exchange, and same token across different exchanges. The results demonstrate clear evidence of sub-second lead-lag patterns across cryptocurrencies and exchanges, where Bitcoin and Ethereum are at the lag position in these fast lead-lag dynamics. Our results suggest that the diffusion of information across these exchanges and tokens is not instantaneous, and the uneven information spread brings lead-lag effects. Further analysis find these lead-lag positions might be correlated with order book resilience. Moreover, we find the lead-lag relationship shows a strong seasonality in intraday patterns where lead-lag effect tend to diminish during opening hours of US stock markets.

The results in chapter four also have implications to cryptocurrency investors and crypto exchanges. The high-frequency lead-lag relationships in crypto market could possibly provide useful and fast information on forecasting possibility and accuracy of cryptocurrency price, improving trading strategy as in traditional market (Alsayed and McGroarty, 2014; Huth and Abergel, 2014). For crypto exchanges, the intraday seasonality of lead-lag effects could give them new insight that attracting more investors globally might help to avoid long lag-length in mid night and speed up the information transmission when US market is closed.

5. 2. Limitations and suggestions for future research

The thesis has studied and investigated the volatility spillovers from related external markets to stablecoins markets, the mispricings of stablecoins allowing arbitrage across-exchanges and the high-frequency lead-lag relationships in crypto markets. However, there are still some limitations in the analysis of this thesis and future research and investigations could be extended further to provide more in-depth understanding in cryptocurrency market to fix these limitations.

In Chapter two, we only measure the volatility spillovers from limited number of markets to four leading stablecoin markets. Future research could investigate the spillover effects between stablecoin markets and more related markets, for example, stock markets in areas other than US, commodity markets including futures markets, gold markets, or other major currencies markets, providing a more comprehensive understanding on volatility transmission mechanism from external markets to stablecoin markets. Also, future research could consider other types of stablecoins such as commodity-collateral and algorithm stablecoins, investigating how shocks from related markets transmit impact different kinds of stablecoins. Further, chapter two assesses volatility spillovers through VAR model. In further studies, different methods could be applied to increase the robustness of analysis. For example, GARCH model, especially dynamic conditional correlation (DCC) GARCH model could be used to measure the volatility spillovers (Antonakakis, 2008).

In chapter three, we investigate mispricings of two leading stablecoins across three top centralized exchanges. Future studies could includes more stablecoins and more exchanges. Also, decentralized exchanges could be considered to see if these cross-exchanges arbitrage opportunities existed on-chain. Moreover, in this chapter we set a relative safe threshold of durations, which is 1 second. Future studies could investigate the trading speed and latency further and try to detect arbitrage opportunities with short durations, which might bring higher profitability. Furthermore, the profit of this arbitrage strategy largely depends on the trading fee levels that arbitrageurs face, future studies might calculate the profitability of arbitrage opportunities under multiple levels of trading fee.

In chapter four, we analyze the high-frequency lead-lag relationships in crypto markets., and these findings might provide useful informations to investors to build a trading strategy. In this regard, future studies could try to develop practical trading strategies which rely on the fast lead-lag relationships in crypto markets. By trying to predict the price of lagged assets and explore arbitrage trading with high-frequency cryptocurrency data, future studies could provide more refined insights into the practical trading strategy and mechanics of information diffusion across markets. Also, further analysis could cover a longer sample period to investigate if and how the high-frequency lead-lag relationships evolve over time, and their potential drivers.

Overall, we acknowledge these above limitations in this thesis and propose several possible directions for future research. We hope these suggestions could advance our future studies and further understandings in cryptocurrency markets.

Appendice

Appendix B.1. Mispricing Frequency by Month in sample period.

Panel A	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Kraken and Bitstamp	131	97	17	33	384	798	999	265	31	16	2326	1175	6272
Kraken and BinanceUS	6	1	1	4	104	3	4	3	0	1	127	8	262
Bitstamp and BinanceUS	10	6	3	26	85	237	321	767	15	0	2402	610	4482

Panel B	2023 Jan	2023 Feb	2023 Mar	2023 Apr	2023 May	2023 Jun	Total
Kraken and Bitstamp	332	122	2243	376	43	21	3137
Kraken and BinanceUS	6	3	100	11	2	2	124
Bitstamp and BinanceUS	146	12	2187	47	8	4	2404

Appendix B.1 displays the numbers are mispricings happened in each combination of exchanges during sample period, included USDT mispricings and USDC mispricings. Panel A displays the results relate to the January 1st, 2022–December 31st, 2022 period. Panel B displays the results related to the January 1st, 2023–June 30th, 2023 period.

Appendix. B.2. Arbitrage Instances and Net Profits under Different Trading Fees.

This plot presents the frequency and net profit of arbitrage opportunities between Kraken and Bitstamp, and between Bitstamp and BinanceUS. The results relate to the January 1st 2022 – June 30th 2023 period, under all possible levels of trading fees.

Appendix B.3. Determinants of Instances and Profits of Arbitrage of USDC between Kraken and Bitstamp.

		K-overpriced, Bit-underpriced	K-underpriced, Bit-overpriced
Panel A: Determinants of Instances of Arbitrage			
Kraken	Spread	0.482	1.018
	Trading volume	11.570***	2.960**
	Order imbalance	-3.129***	-1.752***
	Adjusted R-square	0.115	0.012
Bitstamp	Spread	0.405	-0.809
	Trading volume	12.979***	9.706**
	Order imbalance	-1.999***	-1.179***
	Adjusted R-square	0.04	0.013
Panel B: Determinants of Arbitrage			
Kraken	Spread	-0.009	-0.022
	Trading volume	0.508***	0.124**
	Order imbalance	-0.034***	0.038**
	Adjusted R-square	0.317	0.075
Bitstamp	Spread	0.118***	0.124***
	Trading volume	0.278***	0.174**
	Order imbalance	-0.032**	-0.020
	Adjusted R-square	0.188	0.143

This table shows the results of regressions of determinants of arbitrages of USDC between Kraken and Bitstamp on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependant variable that equals one on days an arbitrage opportunity is created and zero otherwise. K-overpriced (Bit-overpriced) denotes USDC in Kraken (Bitstamp) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.4. Determinants of Instances and Profits of Arbitrage of USDT between Kraken and BinanceUS.

		K-overpriced, Bin-	K-underpriced, Bin-overpriced
Panel A: Determinants of Instances of Arbitrage			
Kraken	Spread	-1.675	-5.773
	Trading volume	7.094***	11.849***
	Order imbalance	-6.374***	-9.271***
	Adjusted R-square	0.039	0.244
BinanceUS	Spread	1.008	0.531
	Trading volume	3.206	6.975*
	Order imbalance	-4.476***	-6.298***
	Adjusted R-square	0.197	0.101
Panel B: Determinants of Arbitrage			
Kraken	Spread	0.852***	0.977***
	Trading volume	0.148***	-0.018**
	Order imbalance	-0.020**	-0.004**
	Adjusted R-square	0.516	0.950
BinanceUS	Spread	0.030	0.045***
	Trading volume	0.847***	0.819***
	Order imbalance	-0.012**	-0.0264***
	Adjusted R-square	0.424	0.859

This table shows the results of regressions of determinants of arbitrages of USDT between Kraken and BinanceUS on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependant variable that equals one on days an arbitrage opportunity is created and zero otherwise. K-overpriced (Bin-overpriced) denotes USDT in Kraken (BinanceUS) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.5. Determinants of Instances and Profits of Arbitrage of USDC between Kraken and BinanceUS.

		K-overpriced, Bin-	K-underpriced, Bin-overpriced
Panel A: Determinants of Instances of Arbitrage			
Kraken	Spread	3.838**	3.189*
	Trading volume	2.526	1.801
	Order imbalance	-7.379***	-7.034***
	Adjusted R-square	0.361	0.122
BinanceUS	Spread	-1.515	4.399**
	Trading volume	11.544***	6.283*
	Order imbalance	-9.832***	-8.549***
	Adjusted R-square	0.086	0.023
Panel B: Determinants of Arbitrage			
Kraken	Spread	0.252***	-0.024
	Trading volume	0.112***	0.085***
	Order imbalance	-0.043***	0.002
	Adjusted R-square	0.291	0.02
BinanceUS	Spread	-0.044	0.987***
	Trading volume	0.243***	0.072***
	Order imbalance	-0.015**	-0.003
	Adjusted R-square	0.101	0.892

This table shows the results of regressions of determinants of arbitrages of USDC between Kraken and BinanceUS on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependant variable that equals one on days an arbitrage opportunity is created and zero otherwise. K-overpriced (Bin-overpriced) denotes USDC in Kraken (BinanceUS) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.6. Determinants of Instances and Profits of Arbitrage of USDT between Bitstamp and BinanceUS.

		Bit-overpriced, Bin-	Bit-underpriced, Bin-overpriced
Panel A: Determinants of Instances of Arbitrage			
Bitstamp	Spread	27.903	22.466
	Trading volume	3.328***	3.956***
	Order imbalance	-3.643***	-6.067***
	Adjusted R-square	0.026	0.012
BinanceUS	Spread	0.987	-1.022
	Trading volume	3.178	4.925*
	Order imbalance	-2.586***	-4.238***
	Adjusted R-square	0.053	0.098
Panel B: Determinants of Arbitrage			
Bitstamp	Spread	-0.017	-0.047
	Trading volume	0.211***	0.112***
	Order imbalance	-0.027***	-0.017**
	Adjusted R-square	0.226	0.087
BinanceUS	Spread	-0.019	0.011
	Trading volume	0.441***	0.418***
	Order imbalance	0.004	-0.011**
	Adjusted R-square	0.137	0.175

This table shows the results of regressions of determinants of arbitrages of USDT between Bitstamp and BinanceUS on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependant variable that equals one on days an arbitrage opportunity is created and zero otherwise. Bit-overpriced (Bin-overpriced) denotes USDT in Bitstamp (BinanceUS) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.7. Determinants of Instances and Profits of Arbitrage of USDC between Bitstamp and BinanceUS.

		Bit-overpriced, Bin-	Bit-underpriced, Bin-overpriced
Panel A: Determinants of Instances of Arbitrage			
Bitstamp	Spread	-1.182*	0.078
	Trading volume	8.988**	13.998***
	Order imbalance	-2.644***	-4.112***
	Adjusted R-square	0.053	0.020
BinanceUS	Spread	-3.166	82.934
	Trading volume	2.312	6.721***
	Order imbalance	-3.088***	-4.355***
	Adjusted R-square	0.092	0.022
Panel B: Determinants of Arbitrage			
Bitstamp	Spread	0.091***	0.052
	Trading volume	0.271***	0.318***
	Order imbalance	-0.035***	-0.014
	Adjusted R-square	0.140	0.105
BinanceUS	Spread	-0.042	0.081***
	Trading volume	0.113**	0.126**
	Order imbalance	0.021**	-0.023**
	Adjusted R-square	0.041	0.102

This table shows the results of regressions of determinants of arbitrages of USDC between Bitstamp and BinanceUS on daily basis, the results relate to the January 1st 2022 – June 30th 2023 period. Panel A presents the determinants of arbitrage occurrence, Panel B presents determinants of arbitrage profit. Spread is the average of quoted spreads over time throughout each day, trading volume is the daily total trading volume, order imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two. Panel B results are based on a logit regression of a dependant variable that equals one on days an arbitrage opportunity is created and zero otherwise. Bit-overpriced (Bin-overpriced) denotes USDC in Bitstamp (BinanceUS) is overpriced. These variables passed the ADF test and VIF test for stationary and multicollinearity. Significant at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.8. Market characteristics of USDC in Kraken and Bitstamp.

	Kraken			Bitstamp		
	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5
Panel A : Kraken-overpriced, Bitstamp-underpriced (328)						
Spread	1.61%	3.5%*	2.9%*	**85.7%*** **	**93.72%*** **	**63.1%*** **
Depth	**-19.3%*** **	**-22.5%*** **	**-19.9%*** **	**-34.3%*** **	**-37.9%*** **	**-34.9%*** **
OIB	-1.8%	0.5%	-5.73%**	-2.92%	**14.5%*** **	**19.9%*** **
Trading volume	**127.3%**	**304.5%**	**44.2%**	**450.4%*** **	**1897.7%*** **	**154.4%*** **
Return std	9.4%***	**19.3%*** **	**11.7%*** **	**205.2%*** **	**436.9%*** **	**236.9%*** **
Panel B : Kraken-underpriced Bitstamp-overpriced (344)						
Spread	2.9%	2.4%	1.97%*	**67.0%*** **	**73.9%*** **	**58.2%*** **
Depth	**-11.8%*** **	**-11.7%*** **	**-10.8%*** **	**-18.8%*** **	**-22.7%*** **	**-32.8%*** **
OIB	-1.5%	5.9%***	1.9%	-6.3%***	-4.5%***	**-25.5%*** **
Trading volume	-7.6%**	**96.7%*** **	**62.3%*** **	**452%*** **	**1707.6%*** **	**151.8%*** **
Return std	4.28%	**19.8%*** **	**15.1%** **	**132.6%*** **	**304.8%*** **	**198.6%*** **

This table presents percentage increases (positive) or decreases (negative) of market microstructure factors when mispricing of USDC occurs between Kraken and Bitstamp. The changes are based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.9. Market characteristics of USDT in Kraken and BinanceUS.

	Kraken			BinanceUS		
	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5
Panel A : Kraken-overpriced, BinanceUS-underpriced						
Spread	**69.9%*****	**68.1%*****	**54.5%*****	**102.3%*****	**95.9%*****	**92.9%*****
Depth	**-58.2%*****	**-61.7%*****	**-71.1%*****	3.1%**	-0.94%	5.2%**
OIB	-2.8%	-3.0%	**-15.4%**	**14.9%*****	**16.4%*****	2.9%
Trading volume	**192.7%*****	**221.9%*****	**112.9%*****	**345.8%*****	**942.9%*****	**684.4%*****
Return std	**77.1%*****	**63.7%*****	**69.7%*****	**27.9%*****	**25.8%*****	**28.9%*****
Panel B : Kraken-underpriced BinanceUS-overpriced						
Spread	**33.9%*****	**51.2%*****	**85.0%*****	**50.8%*****	**48.2%*****	**65.0%*****
Depth	**-65.1%*****	**-75.4%*****	**-78.9%*****	**48.5%****	**41.0%****	**26.6%***
OIB	**-14.8%****	**18.0%*****	**25.6%*****	**-15.2%*****	**-24.7%*****	**-12.4%*****
Trading volume	**165.6%*****	**344.5%*****	**222.3%*****	**1037.7%*****	**1396.9%*****	**1086.7%*****
Return std	**55.8%*****	**175.9%*****	**61.0%*****	**57.8%*****	**58.7%*****	**66.4%*****

This table presents percentage increases (positive) or decreases (negative) of market microstructure factors when mispricing of USDT occurs between Kraken and BinanceUS. The changes are based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.10. Market characteristics of USDC in Kraken and BinanceUS.

	Kraken			BinanceUS		
	t_0-5 to t_0-2	t_0-1 to t_1+1	t_1+2 to t_1+5	t_0-5 to t_0-2	t_0-1 to t_1+1	t_1+2 to t_1+5
Panel A : Kraken-overpriced, BinanceUS-underpriced						
Spread	9.2%***	**16.8%*** **	**52.6%*** **	**39.1%*** **	**85.6%*** **	**34.3%*** **
Depth	**-58.7%*** **	**-44.1%*** **	**-35.6%*** **	**18.4%* **	**-11.5%*** **	-0.11%
OIB	**18.1%*** **	**-32.9%*** **	**-8.3%*** **	**24.0%*** **	5.6%**	**29.4%*** **
Trading volume	**462.1%*** **	**866.1%*** **	**631.2%*** **	**1296.7%*** **	**1746.7%*** **	**227.7%*** **
Return std	**41.0%*** **	**25.5%** **	**124.1%*** **	**219.4%*** **	**233.4%*** **	**148.5%*** **
Panel B : Kraken-underpriced BinanceUS-overpriced						
Spread	5.1%***	**44.6%*** **	**42.1%*** **	**53.9%*** **	**64.8%*** **	**84.5%*** **
Depth	**-44.2%*** **	**-47.3%*** **	**-47.1%*** **	**32.9%* **	**-39.4%*** **	**-36.1%*** **
OIB	**32.7%*** **	2.2%	-1.1%	**17.6%** **	-7.4%**	**-10.5%*** **
Trading volume	**45.3%*** **	**467.4%*** **	**136.5%*** **	**373.2%*** **	**126.5%*** **	**342.9%*** **
Return std	30.3%	**20.6%*** **	**32.1%*** **	**209.2%*** **	**719.0%*** **	**812.9%*** **

This table presents percentage increases (positive) or decreases (negative) of market microstructure factors when mispricing of USDC occurs between Kraken and BinanceUS. The changes are based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.11. Market characteristics of USDT in Bitstamp and BinanceUS.

	Bitstamp			BinanceUS		
	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5
Panel A : Bitstamp-overpriced, BinanceUS-underpriced						
Spread	**161.9%*****	**193.0%*****	**204.2%*****	7.2%***	4.4%**	**19.3%*****
Depth	**-81.9%*****	**-79.1%*****	**-88.9%*****	-2.5%	-3.0%*	-3.3%
OIB	-3.0%***	-7.9%***	**-16.0%*****	9.5%***	**11.5%*****	-2.6%
Trading volume	**96.9%*****	**345.3%*****	**154.3%*****	**71.3%*****	**162.9%*****	**171.7%*****
Return std	**278.3%*****	**759.3%*****	**278.4%*****	**16.1%*****	**13.0%*****	**21.3%*****
Panel B : Bitstamp-underpriced BinanceUS-overpriced						
Spread	**277.3%*****	**286.1%*****	**270.2%*****	0.8%	1.6%	3.6%**
Depth	**-89.5%*****	**-90.1%*****	**-90.3%*****	-5.4%***	-2.6%**	-3.6%***
OIB	**-11.3%****	5.1%***	7.9%***	**-21.6%*****	**-10.2%*****	**-20.3%*****
Trading volume	**43.3%*****	**302.2%*****	**157.9%*****	**191.7%*****	**373.1%*****	**86.1%*****
Return std	**271.2%*****	**454.7%*****	**267.3%*****	**20.8%*****	**15.4%***	18.2%

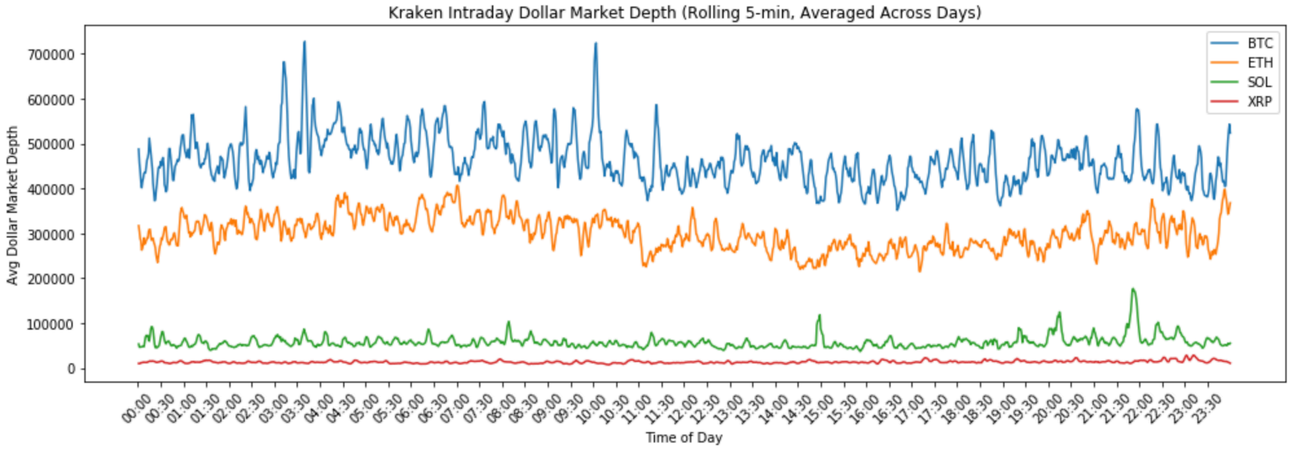
This table presents percentage increases (positive) or decreases (negative) of market microstructure factors when mispricing of USDT occurs between Bitstamp and BinanceUS. The changes are based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix B.12. Market characteristics of USDC in Bitstamp and BinanceUS.

	Bitstamp			BinanceUS		
	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5	t_0-5 *to* t_0-2	t_0-1 *to* t_1+1	t_1+2 *to* t_1+5
Panel A : Bitstamp-overpriced, BinanceUS-underpriced						
Spread	**64.7%*****	**76.3%*****	**85.5%*****	-4.1%	-4.2%**	-3.2%**
Depth	**-36.1%*****	**-60.7%*****	**-49.6%*****	**-13.6%*****	**-12.6%*****	**-10.4%*****
OIB	-7.8%***	12.1%	**-45.7%*****	**11.4%*****	**17.5%*****	**22.7%*****
Trading volume	**422.8%*****	**670.0%*****	**137.4%*****	**65.9%*****	**94.0%*****	**-21.1%*****
Return std	**339.0%*****	**379.2%*****	**174.4%*****	**30.3%*****	**16%***	**25.6%*****
Panel B : Bitstamp-underpriced BinanceUS-overpriced						
Spread	**71.8%*****	**81.8%*****	**81.1%*****	**32.3%*****	**28.0%*****	**32.0%*****
Depth	**-79,4%*****	**-82.6%*****	**-83.5%*****	**-11.1%*****	**-10.7%*****	**-10.1%*****
OIB	2.2%	**11.1%*****	**22.3%*****	2.9%	-3.7%	-9.5%***
Trading volume	**485.9%*****	**1161.3%*****	**121.6%*****	**112.7%****	**100.6%*****	**96.0%*****
Return std	**115.5%*****	**547.1%*****	**370.3%*****	**42.9%*****	**39.6%*****	**10.2%***

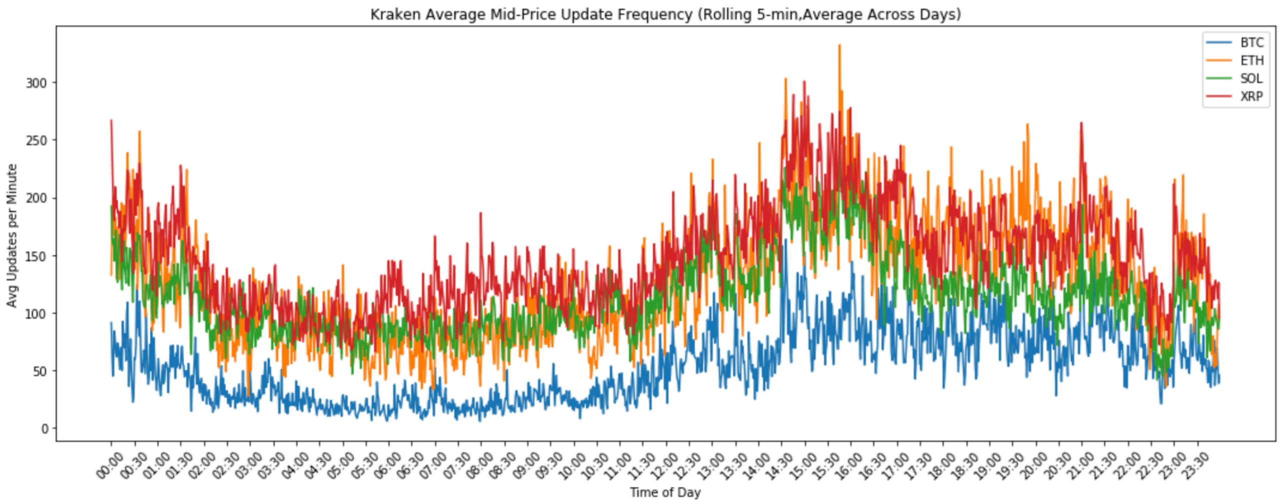
This table presents percentage increases (positive) or decreases (negative) of market microstructure factors when mispricing of USDC occurs between Bitstamp and BinanceUS. The changes are based on the numbers from the same time of the day on the previous 20 trading days without mispricing, if there is a mispricing at the same time of the day in previous 20 trading days we take earlier trading days. The results relate to the January 1st 2022 – June 30th 2023 period. Two arbitrage opportunities occur within 10 minutes will be combined to avoid period overlap. Spread is calculated for the first trade in each interval as two times the absolute value of the difference between the transaction price and the prevailing mid-price (effective spread). Depth is the value of shares at the first level (both the bid and ask) of order book at the start of each interval. Order Imbalance is calculated as the difference in the absolute value between buyer-initiated trades and seller-initiated trades divided by the sum of the two in each interval. Statistical significant changes at the 10% level or higher are in bold. Statistical Significant of bootstrap test at 0.01 '***', 0.05 '**', 0.1 '*'.

Appendix C.1. The intraday dollar-depth of cryptocurrencies in Bitfinex.



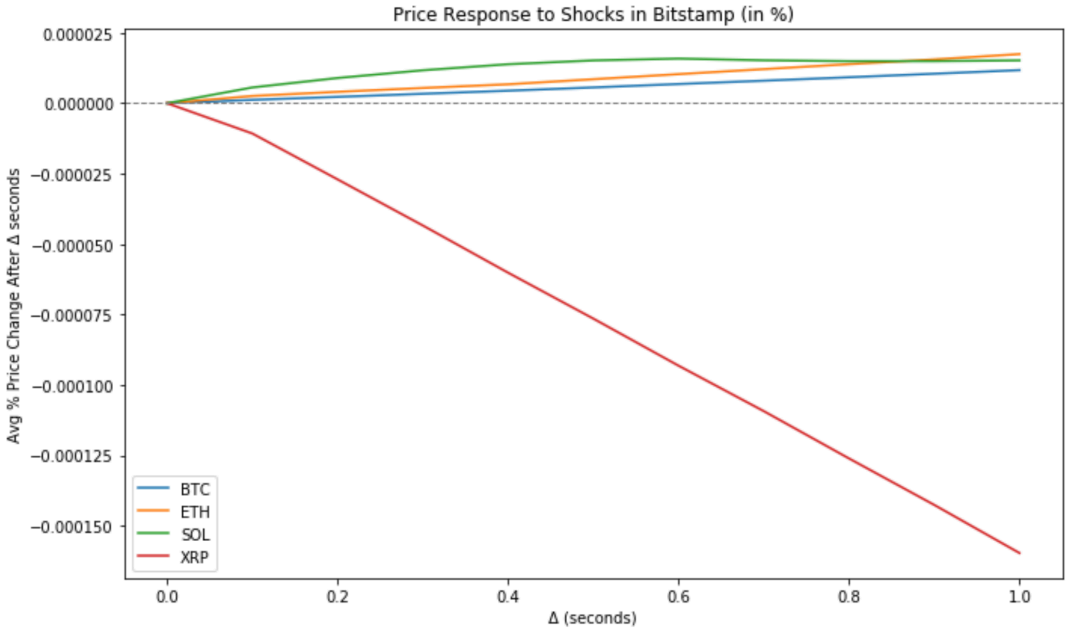
This figure shows the dollar market depth of sample cryptocurrencies in Bitfinex. We calculate this intraday market depth by calculating the one-minute dollar depth with five-minutes rolling window and averaging across all minutes of a trading day over sample period.

Appendix C.2. The intraday mid-price updates frequency of cryptocurrencies in Bitfinex.



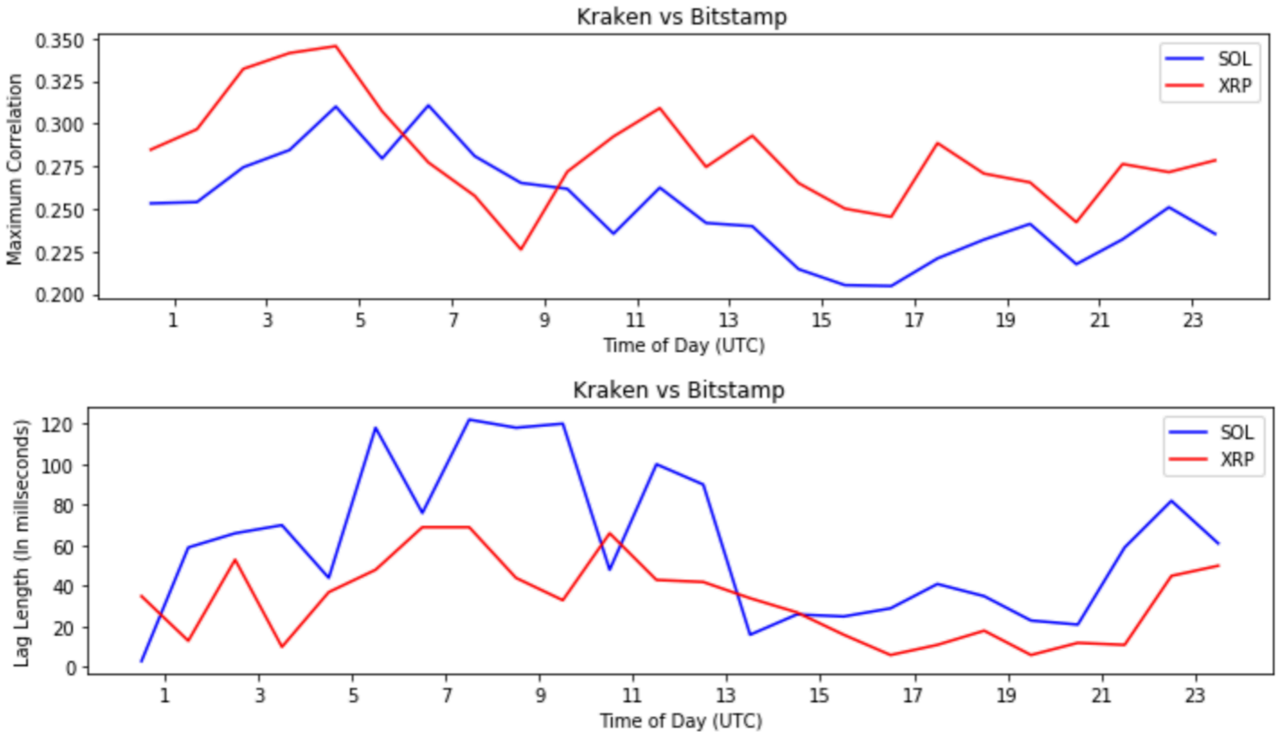
This figure shows Mid-price updates frequency per minute of a day in sample period of each cryptocurrencies in exchange Bitfinex. We calculate this intraday mid-price updates frequency by calculating the numbers of mid-price updates in each minute and averaging across all minutes of a trading day over sample period.

Appendix C.3. The mid-price change percentage of cryptocurrencies in Bitfinex.



Appendix C.3 shows the average mid-price change after Δ seconds of sample cryptocurrencies in exchange Kraken. We calculate the percentage of changes of mid-price from 0.1 second to 1second interval, and then average the results to plot the curves.

Appendix C.4. Intraday Lead-Lag relationship of Kraken and Bitstamp in SOL and XRP.



Appendix C.4 displays the Lead-Lag intraday pattern. Intraday patterns in the Maximum correlation and Lag length of Kraken and Bitstamp in SOL and XRP. The blue and red curves denote SOL and XRP, respectively. The Lag Length denotes the lag time of Kraken, it indicates Kraken lagging Bitstamp if it is positive and Kraken leading Bitstamp if it is negative. Times on the horizontal axes refer to the previous one-hour interval (e.g. 9:30 refers to the 09:00-10:00 interval).

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