The London School of Economics and Political Science

Essays on FinTech and Financial Markets

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 62,018 words.

Statement of conjoint work

I confirm that Chapter 2 was jointly co-authored with Yang You and I contributed 50% of this work.

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Abstract

This thesis contains three essays on FinTech and financial markets.

In the first chapter, I study the business models of cryptocurrency exchanges and their implications for token performance and the cryptocurrency exchange industry dynamics. As the most powerful financial intermediaries in cryptocurrency markets, cryptocurrency exchanges play the dual roles of traditional exchanges and underwriters. Based on two novel measures that capture the hidden heterogeneity of cryptocurrency exchanges, I show that 1) tokens listed in exchanges with large trading revenues perform better, and 2) exchange characteristics predict token returns, with stronger effects for exchanges with large trading revenues. A stylized reputation model shows how the interaction between trading and listing explains differences in token performance. I also argue that first-mover advantages lead to a natural concentration in the cryptocurrency exchange industry.

In the second chapter (co-authored with Yang You), we find that Bitcoin trading is more active in countries where people express more distrust in others. The paper argues that distrust serves as a fundamental for cryptocurrency valuation by exploring price differences in panel data. We proxy for Bitcoin demand with transitory price deviations—Bitcoin prices in a local currency, converted into dollars, relative to the average worldwide dollar Bitcoin prices. A simple portfolio choice model generates several predictions that we test empirically. Price deviations rise when 1) perceptions of institutional failures grow, 2) crypto-trading frictions increase, and 3) cryptocurrency prices rally. Consistent with the model's predictions, distrust explains price response heterogeneity: investors in low-trust countries demand more Bitcoins and drive up its price relative to the world dollar price when local institutional quality deteriorates, arbitrage frictions intensify, and risk appetite rises.

In the third chapter, I construct a measure which captures the evolution of market beliefs based on option data. By tracking market belief updates over time, I find evidence of excess volatility in expected returns in one-month investment horizons. The evidence is inconsistent with expected returns being a martingale. I find no evidence of excess volatility in six-month investment horizons. Based on the dynamics of market beliefs, I measure uncertainty as the time-series volatility of expected returns. I show evidence of an uncertainty premium.

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Chapter 1

The Dual Role of Cryptocurrency Exchanges

This paper studies the business models of cryptocurrency exchanges and their implications for token performance and the cryptocurrency exchange industry dynamics. As the most powerful financial intermediaries in cryptocurrency markets, cryptocurrency exchanges play the dual roles of traditional exchanges and underwriters. Based on two novel measures that capture the hidden heterogeneity of cryptocurrency exchanges, I show that 1) tokens listed in exchanges with large trading revenues perform better, and 2) exchange characteristics predict token returns, with stronger effects for exchanges with large trading revenues. A stylized reputation model shows how the interaction between trading and listing explains differences in token performance. I also argue that first-mover advantages lead to a natural concentration in the cryptocurrency exchange industry.

JEL-Classification: G23, G24, G29.

Keywords: Cryptocurrency Exchanges, Bitcoin, ICO Tokens, Reputation Concerns, Certification Role, Market Segmentation

1.1 Introduction

Cryptocurrency is a new asset class with few institutional investors, investment bankers, and venture capitalists. According to Binance, only 7% of all cryptocurrencies were owned by institutions in 2019.[1] Cryptocurrency exchanges are the most important intermediaries in the blockchain and cryptocurrency ecosystem. Most crypto users trade through exchanges and many entrepreneurs raise funds by listing their tokens on exchanges.[2] In the absence of investment banks, cryptocurrency exchanges play the dual roles of traditional exchanges and underwriters in cryptocurrency markets. In a similar spirit to the Glass-Steagall Act, it is interesting to investigate whether these different activities should be separated and how the two different roles of cryptocurrency exchanges interact with one another. How does the dual role of cryptoexchanges affect the organization of the exchange industry? Is the dual-role business model welfare improving?

My paper is a first attempt at understanding cryptoexchanges' business models and industry dynamics. Cryptocurrency exchanges facilitate trading and also perform a certification role when listing tokens. There are two types of cryptocurrency exchanges, both of which share the same name but focus on different types of businesses.[3] The sources of revenue of these different types of exchanges provide them with differential incentives. I propose two novel measures to capture the hidden heterogeneity of cryptocurrency exchanges. Based on these measures, I show that exchange characteristics are associated with different listing outcomes and token performance. In particular, exchanges' revenue from trading fees appears to play an essential role in their incentives for deciding which token to list, which has important implications for the competitive landscape and the industrial organization of cryptocurrency exchanges.

First, I analyze listing results and token performance across cryptocurrency exchanges based on web traffic measures. I define first-tier exchanges as the top ten exchanges based on reputation, measured by their historical web traffic. The web traffic measure considers an extensive range of variables, including page views, bounce rate, unique visitor count,

[1] Source: https://research.binance.com/.

[2] Listing is analogous to Initial Public Offerings (IPO) in traditional stock markets. According to ICOBench, $27 billion have been raised in 5,728 Initial Coin Offerings (ICOs), and $ 1.7 billion have been raised in 294 Initial Exchange Offerings (IEO) by 2021.

[3] Centralized cryptocurrency exchanges are my focus because they are similar to traditional financial intermediaries, while decentralized exchanges use automatic market maker (AMM) mechanisms built on smart contracts.

time on site, relative ranking, and keyword searches on major search engines. Another set of first-tier exchanges consists of those licensed by the United States with strict know-your-customer (KYC) requirements.

I manually collect each token's listing information and identify the exchange that first lists the token. I then compare tokens' performances over multiple horizons. I consider several performance measures, including tokens' short-term returns, long-term returns, market capitalization, cumulative trading volume, failure rates, and adjusted performance by subtracting Bitcoin's performance. The results show that tokens listed on first-tier exchanges perform better than those on second-tier exchanges under multiple metrics and horizons. In addition, tokens listed on lower-tier exchanges have higher failure rates than those listed on first-tier exchanges. The results suggest that tokens listed on first-tier exchanges are of better quality than those listed on lower-tier exchanges.

Next, I proxy for cryptocurrency exchanges' reputation-building incentives with exchange token characteristics and estimate the correlation between exchange tokens' characteristics and listed tokens' performance. Exchange tokens are those native to the cryptocurrency exchange platform. Such tokens fulfil multiple purposes, including enhancing liquidity, offering trading fee discounts, and facilitating platform governance. Exchange token returns proxy for exchange profitability, which then affects the incentives of cryptocurrency exchanges to set stricter listing standards. In particular, I use the past one-month cryptocurrency exchange token return before the initial listing date for each token as a proxy for exchange quality. I find that past exchange token returns predict higher listed token returns.

I also investigate whether real-time exchange tokens' characteristics affect the daily returns of listed tokens. I consider characteristics such as the past two-week average returns, past two-week average market capitalization changes, and past two-week average trading volume changes. I find that the past two-week exchange tokens' characteristics are associated with (real-time) listed token daily returns. Furthermore, I study cryptocurrency exchange heterogeneity by adding an interaction term based on the first-tier exchange classification. I find that exchange characteristics predict returns and that such effects are stronger for exchanges with more trading revenue.

I note that the empirical analysis may suffer from an endogeneity issue. Thus, my focus is on prediction instead of causality. There are three possibilities for explaining exchange characteristics' ability to predict token returns: (i) First-tier exchanges exert more effort and set high standards in selecting high-quality tokens; (ii) high-quality token issuers prefer to be listed on first-tier exchanges and choose not to be listed on lower-tier exchanges; and (iii) first-tier exchanges cause the better performance of the listed tokens due to enhanced exchange traffic. Empirically, it is challenging to separate the above channels, and all three factors could explain the outperformance of tokens listed on first-tier exchanges. Reverse causality could also be an issue. Thus, I do not try to establish which of these channels explains the results. This paper's key focus is on market structure, competition issues, and the implications of the empirical results for the industrial organization of cryptocurrency exchanges.

The market segmentation of first-tier and lower-tier exchanges indicates that incumbents with first-mover advantages will typically maintain their dominant market shares, thus resulting in a highly concentrated industry. The empirical findings provide evidence for this hypothesis, despite their limitations. The evidence suggests that the interaction between trading and listing affects the incentives of cryptocurrency exchanges. Moreover, another contribution of the chapter is to document the effects of financial intermediaries on token performance. Despite the lack of causal inference, my results suggest that small-cap tokens do not outperform large-cap tokens, in contrast with size effects in the stock markets, where financial intermediaries are less heterogeneous.[4]

To further understand the industry dynamics of cryptocurrency exchanges, I develop a simple theoretical framework based on Mathis et al. (2009). In the model, exchanges that derive most of their revenue from trading have different incentives than those that derive profits mainly from listing. First-tier exchanges have more trading revenue. Because exchange reputation affects trading volume, first-tier exchanges choose to list only high-quality tokens. Because lower-tier exchanges have low trading revenues, they have incentives to list lower-quality tokens. Thus, exchanges face a tradeoff between increasing current revenue and preserving future revenue. Those with more trading revenue are more likely to set high listing standards in order to preserve their reputations. By contrast, exchanges that depend on their listing business typically set lax listing standards. The segmentation of the exchange industry can be caused initially by first-mover

[4] Fama-French size factor SMB (Small-Minus-Big) are well-known in stock markets, which shows that small-cap stocks outperform large-cap stocks. See Liu et al. (2019) and Liu and Tsyvinski (2021) for the discussions on the risk factors in cryptocurrency markets.

advantages. Network externalities create a feedback loop that works as a barrier to entry. From a policy perspective, regulation might be needed if low listing standards lead to the exploitation of unsophisticated investors.

My paper is closely related to three research areas. The first is on cryptocurrency markets. Howell et al. (2020) document that ICO characteristics such as disclosure, credible commitment to the project, and quality signals are associated with successful outcomes. They also find that exchange listing is related to higher future employment.[5] Lee et al. (2022) show that certification by FinTech platform analysts predicts ICO fundraising success and long-run token performance, which also helps detect potential fraud ex-ante. Li et al. (2021) find that pump-and-dump schemes on cryptocurrency exchanges lead to short-term bubbles in cryptocurrency markets and are detrimental to token liquidity and price. Cong et al. (2021a) identify crypto wash trading on 29 cryptocurrency exchanges through tests exploiting robust statistical and behavioral patterns in trading.[6] Aspris et al. (2021) document significant differences in the listing and trading characteristics of tokens listed on centralized and decentralized exchanges. Makarov and Schoar (2021) build a novel database based on on-chain data to analyze the Bitcoin network and its main participants. Makarov and Schoar (2020) highlight that countries with poorly functioning financial institutions or tighter capital controls might value Bitcoin more highly. Foley et al. (2019) find that the illegal share of Bitcoin activity declines with mainstream interest in Bitcoin and with the emergence of more opaque cryptocurrencies. Griffin and Shams (2019) illustrate that Tether is used to provide price support and manipulate other cryptocurrency prices. Liu and Tsyvinski (2021) analyze the risk-return tradeoff of cryptocurrencies and show that momentum and investor attention strongly forecast cryptocurrency returns. Tang and You (2021) document that distrust in local institutions drives excess demand for de-nationalized digital assets across countries. My paper contributes to the literature by establishing a novel intermediary-based channel that is related to the heterogeneity of token performance in cryptocurrency markets.

My paper is also related to a broader literature on blockchain economics.[7] Yermack (2015) discusses whether Bitcoin may serve as a real currency. Harvey (2016) explores the

[5] Li and Mann (2018) develop a model of ICO and platform building. See Li and Mann (2019) for a review of current ICO research and future research directions.

[6] Aloosh and Li (2019) also detect crypto wash trading using the internal data of a major Bitcoin exchange leaked by hackers.

[7] Chen et al. (2021) provide a brief introduction to blockchain economics.

mechanics of cryptofinance and several applications. Budish (2018) proposes a theoretical framework to analyze the economic limits of blockchain. Biais et al. (2019) develop a game theoretical model to understand coordination issues in proof-of-work blockchains. Ferreira et al. (2019) offer a model of blockchain governance and show that in public blockchains that rely on the proof-of-work system, blockchain governance is captured by a large firm. Cong and He (2019) analyze how decentralization relates to consensus quality and how the quintessential features of blockchain change the landscape of competition. Cong et al. (2021b) build a dynamic asset-pricing model of crypto-tokens on blockchain-based platforms. Abadi and Brunnermeier (2018) present a blockchain trilemma and discuss the importance of external trust. Easley et al. (2019) investigate how transaction fees affect the dynamics and stability of Bitcoin. Sockin and Xiong (2020) model cryptocurrency as both a decentralized digital platform developed to facilitate transactions and as an investable asset for speculators. My paper provides evidence of the natural concentration of centralized intermediaries in cryptocurrency markets, highlighting the difficulty in achieving full decentralization in blockchains.

My paper also contributes to the literature on the industrial organization of exchanges.[8] Foucault and Parlour (2004) develop a model where stock exchanges compete for IPO listings and find that competing exchanges can obtain positive expected profits by choosing different trading costs and listing fees in equilibrium. Amira and Muzere (2011) investigate cross-border competition by stock exchanges for firm listings and show that high-growth firms tend to obtain listings on stock exchanges with high listing standards. Draus et al. (2009) find that the level of listing requirements maximizing investor welfare depends on the sensitivity of investors' utility to changes in liquidity and varies with the organization of listing and trading. Treptow and Wagner (2005) document that the relationship between stock exchanges and firms seeking listing has changed dramatically, while some of the functions are now performed by other institutions. Geranio and Lazzari (2013) highlight the monopolistic position of exchanges in the offering and pricing of listing services, and document that US exchanges apply higher fees for medium-sized companies whilst EU exchanges are more expensive for large firms. Budish et al. (2019) build a model of financial exchange competition, showing that exchanges can earn economic

[8]See Floreani and Polato (2013) for the economics of the stock exchange industry. Cantillon and Yin (2011) describes a research agenda related to the competition and market structure of financial exchanges.

profits from selling speed technology, even though exchange trading fees are competitive. Cespa and Vives (2021) argue that the free entry of exchanges delivers superior liquidity and welfare outcomes, but entry can be excessive or insufficient. Baruch and Saar (2009) show that a stock will have higher liquidity when being listed on exchanges where similar securities are traded. Macey and O'Hara (2002) investigates the role and analyze the economics of listing fees and shows how capital market developments have changed the desirability and viability of price structures. Cumming and Johan (2013) document that litigated cases of fraud significantly vary across exchanges within the United States, while by contrast, there is little enforcement comparatively outside the United States. My paper is one of the first to analyze exchanges in cryptocurrency markets, which opens a new strand of study on the industrial organization of cryptocurrency exchanges.

My paper is organized as follows. Section 3.2 introduces the institutional background of cryptocurrency exchanges and cryptocurrency markets. Section 3.3 investigates how the hidden heterogeneity across exchanges and exchange characteristics affect the performance of listed tokens. Section 3.4 provides a model of cryptocurrency exchanges. Section 3.5 discusses the competitive landscape in the cryptocurrency exchange industry. Section 3.6 concludes.

1.2 Institutional Background

1.2.1 Cryptocurrency Exchanges

Cryptocurrency exchanges are the most important financial intermediaries in the blockchain and cryptocurrency world. They allow customers to trade cryptocurrencies for other assets. While in principle, cryptocurrencies can be traded without relying on any intermediaries, it requires specialized technical expertise to access, store, send, and receive cryptocurrencies.[9] Since 2010, cryptocurrency trading platforms have come into play and built a user-friendly marketplace to facilitate cryptocurrency trading, which is the early prototype of current cryptocurrency exchanges.[10] As more types of tokens (e.g.

[9]For example, Bitcoin is designed as a peer-to-peer payment system, where users can send their Bitcoin based on a public-private key mechanism. However, the process is not straightforward for users without adequate knowledge in computer science and blockchain data structure.

[10]The earliest cryptocurrency trading platforms are bitcoinmarket.com and Mt. Gox. After the collapse of Mt. Gox in 2014, more sophisticated cryptocurrency exchanges become further estab-

Altcoins) arise in cryptocurrency markets, there is a furhter boost to the business model of cryptocurrency exchanges.

Nowadays, centralized cryptocurrency exchanges (CEX) still remain the most popular exchanges, while decentralized cryptocurrency exchanges (DEX) have limited market shares despite their rapid growth in recent years.[11] Cryptocurrency exchanges generate income through two main businesses: trading services (like a traditional stock exchange) and listing services (like an investment bank). The cryptocurrency exchange industry is a free-entry market with limited regulation. There are 304 centralized cryptocurrency exchanges listed on coinmarketcap.com as of December 16, 2021, and at least 16,078 exchanges having ever existed around the world.[12]

The cryptocurrency exchange industry is highly concentrated, with a few large players. According to Timestamp Capital (2018), the top 6 exchanges account for 58.8% of the total daily trading volume, while the top 14 exchanges account for 73% of the total daily trading volume. The market size and profitability of cryptocurrency exchanges are comparable to traditional stock exchanges.[13] Cryptocurrency exchanges compete for licenses and also for the right to trade in fiat currencies. By 2020, 6 exchanges in US and 26 exchanges in Japan were licensed. Exchanges with a fiat currency channel can complete trades instantly. Other exchanges can still do fiat-crypto business without a fiat currency channel, but it would take much longer for a trade to be completed. Typically, fiat currency channel regulation is done by forcing cryptocurrency exchanges to open an corporate account in local banks. Many cryptocurrency exchanges cannot establish relationships with local banks, so that they can not do any fiat-crypto business but can only do crypto-crypto business.[14]

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lished. A Brief History of Cryptocurrency Exchanges: https://medium.com/the-capital/a-brief-history-of-cryptocurrency-exchanges-2b48d4531918

[11] DEX has a different business model from CEX, which typically rely on smart contracts to implement transactions. Smart contracts record transactions on the public blockchain, instead of the exchanges' database. Uniswap, the largest DEX, only captures 0.0018% of the market share as of March 28, 2022.

[12] Coinmarketcap.com is one of the most recognized data aggregator in cryptocurrency industry. According to its report in 2019, 16078 exchanges existed around the world. Many exchanges exist before and died later. There are also exchanges that are not listed by Coinmarketcap.com.

[13] The daily dollar volume (Feb 4, 2021) of Binance is $23,554,069,856 (280 coins), Coinbase is $4,595,937,319 (43 coins), and NASDAQ is $260,038,855,074 (4174 stocks). The net income in 2018 of Binance is $458 million (launched in 2017), Coinbase is $520 million (launched in 2012), and NASDAQ is $458 million (launched in 1971)

[14] Fiat-crypto business is to trade between fiat currency and cryptocurrency, e.g. BTC-USD. Crypto-crypto business is to trade between cryptocurrencies, e.g. BTC-ETH.

1.2.2 First-tier Exchanges v.s. Lower-tier Exchanges

Based on their main revenue source, exchanges can be classified into two types: *first-tier exchanges* and *lower-tier exchanges*. First-tier exchanges receive their major proportion of income from trading activities, e.g. trading commissions, withdrawal fees, etc.[15] By contrast, lower-tier exchanges earn their main proportion of income from listing revenue, i.e., the fees that token issuers pay in order to be listed on the exchange.[16] First-tier exchanges tend to be early entrants in the industry, while lower-tier exchanges are typically newcomers who have been operating for fewer than three years.

Another major difference between first-tier and lower-tier exchanges is that they focus on different groups of currencies. First-tier exchanges mostly focus on the major currencies such as Bitcoin, Ethereum, Tether, etc., while lower-tier exchanges focus more on small and new currencies, which have lower liquidity and market capitalization. Compared to first-tier exchanges, lower-tier exchanges derive a larger proportion of their revenues from listing services instead of trading services. This is because few investors use lower-tier exchanges to trade major currencies such as Bitcoin and Ethereum. First-tier exchanges also offer listing services, but they only list tokens that are more likely to have real potential. Compared to lower-tier exchanges, they have more stringent listing requirements, charge higher listing fees, and conduct stricter due diligence. In contrast, lower-tier exchanges focus on listing revenue, so their listing standards are typically laxer to attract listing business.[17]

[15] For example, largest cryptocurrency exchanges such as Coinbase, Binance, Huobi, Bitfinex, and Kraken are classified as first-tier exchanges.

[16] There are a large number of lower-tier exchanges, e.g. Probit, Coineal, Coinbene, OEX, Digifinex, CoinBit, Coinsbank, OOOBTC, RightBTC, Dobi trade, Simex, CoinZest, etc.

[17] Anecdotal evidence shows that many lower-tier exchanges are involved in pyramid selling of the small tokens, which is a new form of online pyramid selling and Ponzi scheme under the disguise of cryptocurrency. Many lower-tier exchanges do not conduct due diligence, although they claim otherwise. Their main incentive is to earn the listing income, thus the main criterion is whether there are enough potential token buyers to trade in the platform for the particular token, so that the exchange can potentially earn more trading fees from the listed tokens. The pyramid selling of the tokens is typically organized off-line (or in Facebook/Wechat/Telegram group) before listing. Once the selling group find enough buyers, they will contact the lower-tier exchanges for their listing services. There are plenty of cases in which the founders of lower-tier exchanges have been arrested for taking part in such schemes. Hence, many lower-tier exchanges have only a short life.

1.2.3 Crypto Wash Trading

Although cryptocurrency exchanges have different business models, investors may find it difficult to distinguish exchanges of different types due to the practice of cryptocurrency wash trading. Wash trading occurs when a trader or investor buys and sells the same securities multiple times in a short period to deceive other market participants about an asset's price or liquidity. It is difficult to monitor wash trading.[18] Moreover, the cryptocurrency exchange industry is lightly regulated and there are no rules to prevent wash trading.

When choosing an exchange, investors may consider trading volumes data as an indicator of exchange quality and credibility. In order to attract more investors, some cryptocurrency exchanges may resort to wash trading to boost their trading volume. A large proportion of lower-tier exchanges' trading volume is due to wash trading and some investors may be misled by the inflated trading volume. According to the Blockchain Transparency Insitute, in 2018, over 80% of top BTC-Pair trading volume was due to wash trading. On Coinbene, OEX, Digifinex, CoinBit, Coinsbank, OOOBTC, RightBTC, Dobi trade, Simex, and CoinZest, up to 99% of volume is achieved via wash trading. In 2019, global wash trading was reduced by 35.7%.

It is worth noting that, although there is little real trading volume, there is significant listing activity on lower-tier exchanges.

1.2.4 Financing Through Tokens

Financing through tokens can be done in different ways, such as Initial Coin Offerings (ICO), Initial Exchange Offerings (IEO), Stock Token Offerings (STO), and exchange listing. An ICO is a type of blockchain-based crowdfunding in which a company seeks to raise money to create a new token, app, or service. Interested investors can buy into the offering and receive the new token through a smart contract. The token may be a utility token (i.e., it can facilitate the use of a product or service), or it may be a security token (i.e., a stake in the company or project). ICOs are highly risky, as they are typically based only on white papers and website information, normally without any details on functional products.

[18] See Cong et al. (2021a) and Aloosh and Li (2019) for recent studies on cryptocurrency wash trading.

An exchange listing is similar to Initial Public Offerings (IPO) in the stock market. Since there are few investment banks and institutional investors in cryptocurrency markets, cryptocurrency exchanges also have to perform the role of the underwriter, conduct due diligence, and select the tokens to be listed. After listing, investors can trade the tokens in the centralized exchanges. Listing can provide token issuers with liquidity and better financing. However, it also provides opportunities for "pump and dump" schemes. There might be an ICO or multiple rounds of financing before a token is listed on a exchange.

IEOs have become more popular recently. IEOs are a combination of an ICO and an exchange listing. The difference between ICOs and IEOs is that the project team conducts the fundraising in an ICO, while in an IEO, fundraising is conducted through the exchange's platform. In addition, exchanges perform a monitoring role in IEOs.

A STO is a form of token-based financing on a regulated traditional stock exchange. It is still under early trials and there are only few examples in the world.

Broadly speaking, cryptocurrencies can be classified into three types: mainstream coins (e.g. Bitcoin, Ethereum, Tether), issued tokens (from ICOs/IEOs), and exchange tokens (e.g. Binance Token, Huobi Token). Mainstream coins are those that are traded by the majority of investors. Typically, they were not issued to finance a particular project. In contrast, tokens (from ICOs/IEOs) are issued by entrepreneurs to finance their projects. Exchange tokens are those native to a cryptocurrency exchange platform. They can fulfil multiple purposes, such as enhancing liquidity, offering trading fee discounts, and facilitating platform governance. As of 1 January 2021, there were 139 exchange tokens.[19] Figure 1.1 shows the total market capitalization of cryptocurrency markets, with and without Bitcoin, from 2015 to 2021. The similar pattern between Bitcoin and altcoins indicates that Bitcoin returns may be a good proxy for a "cryptocurrency market factor."

1.3 Empirical Analysis

This section presents the main empirical analysis.

[19]For example, Binance Token (BNB) is issued by Binance exchange and Huobi Token (HT) is issued by Huobi exchange. Not all cryptocurrency exchanges issue an exchange token, e.g., Coinbase.

1.3.1 Data Description

The ICO and IEO data of tokens are from TokenData and ICO Bench.[20] I obtain daily cryptocurrency trading data from Coinmarketcap and Coingecko, including price, market capitalization, and trading volume. Cryptocurrency listing data is from ICO Bench, Coinmarketcap, Coingecko, Twitter, project official websites, and blockchain media platforms. Cryptocurrency exchange data is also from Coinmarketcap. Cryptocurrency regulation data is from New York State Department of Financial Services (NYSDFS). Web traffic data is from Similar Web and Coinmarketcap.

The sample includes 1,765 tokens from 2014 to 2020.[21] There are 664 coins listed in total, and 199 of them are listed on first-tier exchanges. Figure 1.2 shows the listed tokens by year in my sample. Table 1.1 reports the summary statistics and distributions of token listed on the cryptocurrency exchanges. Over 50% of the tokens generate a negative average return in both short-term and long-term horizons, while over 75% of the tokens have negative returns in the long-term.

I classify cryptocurrency exchanges based on two different measures: (1) web traffic and (2) exchange token performance. I use these measures to predict token performance.

1.3.2 Token Performance Across Exchanges: Web Traffic

Similar to Cong et al. (2021a), I define first-tier exchanges as the top ten exchanges based on reputation, measured by web traffic. The ranking of exchanges is based on historical web traffic data from Coinmarketcap and SimilarWeb on 1 January of each year. A large number of retail traders (i.e. buyers and sellers) are required for an exchange to have high trading volumes.[22] The web traffic factor takes into account several variables, including page views, bounce rate, unique visitor count, time on site, relative ranking, and keyword searches on major search engines.

To investigate how the web traffic measure of reputation relates to other measures of exchange reputation, I compare the mean of average liquidity, number of coins, number of

[20]TokenData and ICO Bench are the most widely used datasets in ICO related research. I use the same ICO sample as Howell et al. (2020).

[21]1520 tokens are from ICO, while 245 tokens are from IEO.

[22]Trading volume data may not be reliable due to crypto wash trading, see e.g., Cong et al. (2021a) and Aloosh and Li (2019).

markets, trading volume, and weekly visits of first-tier and lower-tier exchanges defined based on web traffic measure. Figure A.1 - A.5 plots the the mean of average liquidity, number of coins, number of markets, trading volume, and weekly visits of first-tier and lower-tier exchanges in 2017, 2018, 2019, and 2020, respectively. First-tier exchanges are defined as the top 10 exchanges based on the web traffic measure, while lower-tier exchanges are the 10 exchanges ranking from 11 to 20. From the figures we can see that exchanges with higher web traffic have larger average liquidity, number of coins, number of markets, trading volume, and weekly visits. The figures also show that reputation is persistent, with first-tier exchanges scoring highly consistently over time.

I also consider cryptocurrency exchanges that are regulated by the United States as first-tier exchanges. These exchanges are licensed to operate in cryptocurrency markets and have strict KYC requirements. I add the KYC exchanges to the set of first-tier exchanges after their licensing dates.[23]

For each token, I manually collect the information of its listing to identify the exchange that first lists the token.[24] I collect listing information from historical trading archives around the date of listing, official project websites, projects' twitter pages, and blockchain media platforms. I consider several performance measures: short-term token returns, long-term token returns, token market capitalization, token cumulative trading volume, and token failure rate. In addition, I construct adjusted performance measures by subtracting the corresponding Bitcoin's performance measure.

Tables 1.2, 1.3, and 1.4 report the results of the following regressions:

$$Y_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is a dummy of whether the coin is listed on a first-tier exchange, and Y_i denotes short-term log returns, long-term log returns, log market capitalization, or log cumulative trading volume.

$$Adj\_Y_i = \alpha + \beta First_i + \epsilon_i$$

[23] Coinbase: 2017-01, Gemini: 2015-10, Itbit: 2015-05, Bakkt: 2019-08, Bitflyer: 2018-11, Bitstamp: 2019-04.

[24] Some tokens are listed on multiple exchanges. In this case, I use the exchange that lists the token first. Since token issuers have to pay a large amount of listing fees, listing in many exchanges does not happen very often.

where $Adj\_Y_i = Y_i - Y_{BTC}$ is the adjusted performance measure by subtracting corresponding performance of Bitcoin.

Specifically, I compare the performance of tokens that are listed on first-tier and lower-tier exchanges after 1, 3, 7, 14, 21, 30, 60, 90, 180, 360, and 720 days from their initial listings. Performance horizon thus vary from 1 day to 720 days. The first two rows report the results for raw performance measures, while the last two rows report the results for adjusted performance. The results show that the tokens listed by first-tier exchanges outperform those listed by lower-tier exchanges across different performance measures. In particular, within the first two weeks after the initial listing, there is no significant difference in token return across the two types of tokens. These findings suggest that the outperformance of first-tier listed tokens is more likely driven by selection than by the popularity of cryptocurrency exchanges. After 1 month from the initial listing, the difference in average log returns and average adjusted log returns of first-tier and lower-tier listed tokens are 6.66% (t = 2.91) and 5.79% (t = 2.68), respectively. As time goes by, the effect becomes more pronounced. After 6 months from the initial listing, the corresponding return differences increase to 8.02% (t = 5.33) and 8.70% (t = 5.24), respectively. After 1 year from the initial listing, the corresponding return differences increase to 4.29% (t = 5.98) and 4.21% (t = 6.90), respectively. After 2 year from the initial listing, the differences are amplified to 6.48% (t = 6.66) and 7.87% (t = 6.40), respectively.

The log market capitalization and log cumulative trading volume across exchanges exhibit similar patterns. After 1 year from the initial listing, the differences between the average token market capitalization across exchanges are 2.434 (t = 14.27) and 2.441 (t = 12.28), while the difference between the average cumulative trading volume are 2.525 (t = 14.73) and 2.627 (t = 14.47). There is an amplifying effect as time goes by.

In the Appendix, I run the same regressions with added controls for listed date (year and month), USD raised in ICO, initial sale price, and exchange fixed effects. These covariates potentially capture individual characteristics and fundamentals for each token, and also take into account seasonality effects in cryptocurrency markets. Table A.1 reports these robustness checks, showing similar results.

In order to test whether the outperformance of the tokens listed on first-tier exchanges is driven by exchange-level token selection risk, I run the following regressions:

$$SD_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and SD_i stands for the volatity of token returns, and

$$AdjSD_i = \alpha + \beta First_i + \epsilon_i$$

where $AdjSD_i = SD_i - SD_{BTC}$.

Table 1.5 compares the aggregate volatility of tokens that are listed by first-tier and lower-tier exchanges 30, 60, 90, 180, 360, and 720 days after their initial listing. It shows that there is no significant difference between the aggregate volatility of the tokens that are listed by the two types of cryptocurrency exchanges. Thus, the better performance of first-tier tokens does not appear to be driven by risk.

My measure captures the risk coming from each cryptocurrency exchange where tokens are listed. The standard error measure captures how risky exchanges are when selecting tokens to be listed, i.e., the aggregate volatility of listed tokens at the exchange level. I acknowledge that the standard deviation may not capture every dimension of risk perfectly and that there are other ways to measure risk. For example, an alternative is to use ARCH or GARCH to model each token's risk, then aggregate all measures into an exchange-based measure. However, this would require additional assumptions and represent a departure from the focus of this paper. My study investigates the cryptocurrency exchange industry and the impact of conglomerate intermediaries on listed tokens. Despite its limitations and simplicity, the standard deviation measure can reflect the volatility of listed token performance at the exchange level. Minimum assumptions are required with this approach. I leave the use of more advanced individual token risk measures for future study.

In addition to the absolute performance measures, I also use the failure rate as an alternative performance measure. The failure rate is calculated based on changes in token prices and trading volume. Define

$$Ratio = \frac{X_t}{X_0}$$

where X_0 denotes either the token price or the trading volume at the initial listing and X_t denotes either token price or trading volume t months after initial listing. I define failure as a Ratio of less than 10%. The failure rate captures another dimension of quality. A significant drop in the token price or trading volume indicates that the token is unlikely to be a high-quality token.

Figures 1.3 and 1.4 show the price ratio of tokens listed by first-tier exchanges and lower-tier exchanges in 1, 6, and 12 months after the initial listing. The distribution shows that tokens listed on lower-tier exchanges have a higher failure rate than those listed on first-tier exchanges. After 1 month, 2 tokens listed by first-tier exchanges fail, while 33 tokens listed by lower-tier exchanges fail. After 6 months, 22 tokens listed by first-tier exchanges fail, while 186 tokens listed by lower-tier exchanges fail. After 1 year, 43 tokens listed by first-tier exchanges fail, while 245 tokens listed by lower-tier exchanges fail. Figures 1.5 and 1.6 display the trading volume ratio of tokens listed by first-tier exchanges and lower-tier exchanges in 1, 6, and 12 months after the initial listing. The patterns are similar to the price ratio. After 1 month, 27 tokens listed by first-tier exchanges fail, while 138 tokens listed by lower-tier exchanges fail. After 6 months, 41 tokens listed by first-tier exchanges fail, while 209 tokens listed by lower-tier exchanges fail. After 1 year, 46 tokens listed by first-tier exchanges fail, while 223 tokens listed by lower-tier exchanges fail. I note that many low-quality tokens listed by lower-tier exchanges are not in Coinmarketcap's database, so the actual failure rate of tokens can be even larger.

1.3.3 Token Performance Across Exchanges: Exchange Tokens

In addition to the web traffic measure, I consider an alternative measure of exchange quality and reputation: exchange token characteristics. An exchange token is a digital asset that is native to a cryptocurrency exchange. As of 1 January 2021, there were

139 exchange tokens.[25] Exchange owners typically issue exchange tokens to incentivize users to adopt the services of their exchanges. Reputable exchanges with high trading revenue typically would like to maintain the return, market capitalization, and trading volume of their exchange tokens. The characteristics of exchange tokens thus reveal some fundamental information about cryptocurrency exchanges. Therefore, I use variation in exchange tokens to capture exchange heterogeneity.

For all listed tokens, I match them with the corresponding exchange token whenever possible.[26] In my baseline tests, I use the past 1-month exchange token return before the initial listing date for each token as a proxy for exchange quality. The exchange token returns before listing capture the incentive of exchanges to choose listing standards. Similar to the previous subsection, I estimate the effects of past exchange token returns on the returns on tokens listed on the exchange using the following regression:

$$Y_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $Ret_{exchange,t-30\to t-1}$ is the past 1-month exchange token return, Y_i is the short-term log return or long-term log return on the token listed on the exchange, and $\gamma_{exchange}$ is exchange fixed effects. I also consider the adjusted returns:

$$Adj\_Y_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $Adj\_Y_i = Y_i - Y_{BTC}$.

Table 1.6 reports the results of the above regressions. The first two rows report the results for raw performance, while the last two rows report the results for the adjusted performance measure. The results show that higher exchange token returns predict higher returns on those tokens listed on the exchange. In particular, a one-unit increase in exchange token returns corresponds to 2.32% (t = 4.75), 1.73% (t = 2.32), 2.43% (t = 2.04), 3.51% (t = 2.54), 6.95% (t = 2.71) 6.23% (t = 2.34), 25.6% (t = 4.42), 11.0% (t = 2.54) increases in the average log return on listed tokens 1 day, 3 days, 1 week, 2 weeks, 3 weeks, 1 month, 2 month, and 3 months after the initial listing. The adjusted log return

[25]For example, Binance Token (BNB) is issued by Binance exchange and Huobi Token (HT) is issued by Huobi exchange. Not all cryptocurrency exchanges issue an exchange tokens, e.g. Coinbase.

[26]There are also exchanges that do not issue exchange tokens. The tokens listed on these exchanges are not included in the analysis in this part.

exhibits the same pattern. A one-unit increase in exchange token corresponds to 2.36% (t = 4.84), 2.00% (t = 2.70), 2.43% (t = 2.08), 3.41% (t = 2.50), 5.44% (t = 2.13), 3.27% (t = 1.25), 24.1% (t = 4.28), 11.5% (t = 2.73) increases in the average log return on listed tokens 1 day, 3 days, 1 week, 2 weeks, 3 weeks, 1 month, 2 month, and 3 months after the initial listing. The correlation between past exchange token characteristics and token performance in the long run (i.e., 1 year and 2 years) is also positive, although weak. The predictive ability of exchange token returns for listed token returns suggests that exchanges with higher trading profits before listing tend to list tokens of better quality.

In the Appendix, I run the same regressions with controls for listed date (year and month), USD raised in ICOs, initial sale price, and exchange fixed effects. These covariates potentially capture the individual characteristics and fundamentals for each token, and also take into account seasonality effects in the cryptocurrency markets. Table A.2 reports this robustness check, which shows results similar to the previous findings.

In order to test whether the outperformance of the tokens listed on first-tier exchanges is driven by exchange-level token selection risk, I run the following regression:

$$SD_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $Ret_{exchange,t-30\to t-1}$ is the past 1-month cryptocurrency exchange token return, SD_i is the volatility of the token listed on the exchange, and $\gamma_{exchange}$ is exchange fixed effects. I also consider the adjusted returns:

$$AdjSD_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $AdjSD_i = SD_i - SD_{BTC}$.

Table 1.7 reports the results. This table uses the past 1-month exchange token returns as a predictor for listed token aggregate volatility 30, 60, 90, 180, 360, and 720 days after its initial listing. The results show that exchange token returns do not predict tokens' aggregate volatility at the exchange level.

In addition to the short-run and long-run return of the listed tokens, I also look into the relationships between real-time daily exchange characteristics and real-time daily returns on listed tokens. Exchange tokens' characteristics are used as proxies, including past two-week average token returns, past two-week average token market capitalization changes, and past two-week average token trading volume changes. I test whether the returns on listed tokens are related to the exchange token's past performance through the following regressions:

$$Ret_{i,t} = \alpha + \beta X_{i,t-14 \to t-1} + \gamma_i + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return on the listed token, $X_{i,t-14 \to t-1}$ is the past two-week average token returns, past two-week average token market capitalization changes, or past two-week average token trading volume changes, and γ_i is the token fixed effects, and

$$AdjRet_{i,t} = \alpha + \beta X_{i,t-14 \to t-1} + \gamma_i + \epsilon_{i,t}$$

where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ is the daily returns on Bitcoin.

Table 1.8 reports the results of the above regressions. Columns (1)-(3) shows the results for token returns, while Columns (4)-(6) exhibits the results for adjusted token returns. A one-unit increase in the past two-week returns on exchange token is associated with 5.52% (t = 5.42) and 1.27% (t = 4.84) rises in the listed token's daily returns and daily adjusted returns, respectively. A one-unit increase in the past two-week average token log market capitalization changes corresponds to 0.076% (t = 12.91) and 0.047% (t = 7.28) rises in the listed token's daily returns and daily adjusted returns, respectively. A one unit increase in the past two-week average log trading volume changes corresponds to 0.017% (t = 6.88) and 0.024% (t = 7.02) rises in the listed token's daily returns and daily adjusted returns, respectively. The results confirm that listed token returns are related to the characteristics of the corresponding exchange tokens.

In the Appendix, I run the same regression with controls for listing dates (year and month), USD raised in ICOs, initial sale price, and exchange fixed effects. These covariates potentially capture individual characteristics and fundamentals for each token, and also take into account seasonality effects in cryptocurrency markets. Table A.3 reports this robustness check, which shows similar results.

1.3.4 Token Performance Across Exchanges: Heterogeneity

To test the hypothesis that first-tier exchanges care more about their reputations and have stronger incentives for listing better tokens, I consider the heterogeneity across exchanges through interactions:

$$Ret_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return on the listed token, $First_i$ is a dummy variable indicating whether the coin is listed by a first-tier exchange, $X_{i,t-14\to t-1}$ is the past two-week average token returns, past two-week average market capitalization changes, or past two-week average trading volume changes, and γ_i is the token fixed effects. I also consider

$$AdjRet_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \epsilon_{i,t}$$

where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ is the daily return on Bitcoin.

Table 1.9 reports the results. Columns (1)-(3) show the results for token returns, while Columns (4)-(6) exhibit the results for adjusted token returns. Column (1) shows that the returns on listed token increase by 4.25% (t = 3.22) if the past exchange token returns go up by one unit. The coefficient of the interaction term is 0.038 (t = 1.99). Column (4) shows that the returns on listed tokens rise by 3.64% (t = 2.60) if the past exchange token returns increase by one unit. The coefficient of the interaction term is 0.141 (t = 6.66). A similar pattern is found for past log market capitalization changes and past two-week average token trading volume changes. All interaction coefficients are positive and statistically significant, indicating stornger results for first-tier exchanges.

In the Appendix, I run the same regressions with controls for listing dates (year and month), USD raised in ICOs, initial sale prices, and exchange fixed effects. Table A.4 reports this robustness check, which shows similar results.

Although exchange tokens can reflect information about the fundamentals of cryptocurrency exchanges, it is worth noting that they may not be a perfect proxy for exchange quality, as exchange owners may issue exchange tokens for different reasons. There are three reasons to design exchange tokens: increasing exchanges' liquidity, incentivizing users' trading activity, and facilitating exchanges' community governance process. To enhance liquidity, cryptocurrency exchanges can use exchange tokens to reward traders through designated staking programs or by offering tokens proportional to their total trading volume. To incentivize users' trading activity, cryptocurrency exchanges can offer fee discounts based on the number of exchange tokens held in a user's wallet or if users pay their fees by using exchange tokens. In this way, crypto exchanges can incentivize trade, build consumer loyalty, and increase the demand for their native token. To facilitate community governance, cryptocurrency exchanges can issue native tokens to offer users voting rights or exclusive privileges. Rather than providing additional monetary benefits for users, governance tokens are designed to serve the exchanges' future development.

To align with their strategic focus and user needs, cryptocurrency exchanges may have different incentives to issue their native exchange tokens. The weight they place on satisfying various incentives may also vary. It is difficult to empirically decompose exchange token characteristics to identify a perfect measure of exchange quality. However, despite the limitations, the attributes of native exchange tokens are still useful. The empirical findings suggest that exchange characteristics and token performance are related. Moreover, the effect of exchange token characteristics on listed token performance suggests that these characteristics may capture a common risk factor. The asset pricing implications can be further explored in future research.

1.4 Theoretical Framework

This section develops a stylized model of reputational concerns based on Mathis et al. (2009), which illustrates how the interaction between trading and listing affects the incentives of cryptocurrency exchanges. The model explains why exchange characteristics are associated with token performance. In particular, the model describes a trade-off between increasing current revenue and future revenue. Trading revenue from mainstream coins incentivizes truthful listing decision. As a result, those exchanges whose major revenue comes from listing would always set lax standards in underwriting, while exchanges whose major revenue comes from the trading business would always set higher listing standards.

1.4.1 Model Setup

I modify the model setting from Mathis et al. (2009) to illustrate the reputation mechanisms for cryptocurrency exchanges. There are infinite periods and three types of risk neutral agents: cryptocurrency exchanges, token issuers, and (a measure one of) investors. At each period, a cashless issuer needs to raise capital $I < 1$ from investors to finance a complex project. The type of project is unknown to all agents ex-ante, including the issuer. Ex-ante, all agents believe that the project is good with probability γ, or bad with probability $1 - \gamma$. In the baseline model, a bad project defaults with probability 1, and a good project defaults with probability p. This assumption is modified from the baseline model in Mathis et al. (2009), in which the good project defaults with probability 0.[27] The assumption is consistent with the possibility that good token issuers may not necessarily succeed. When not in default, the project yields a return R normalized to 1. The discount rate is normalized to 0. Assume $1 - p > I$, thus the good project should always be financed. Assume $\gamma p < I$, so that no investment happens if investors are uninformed.

The exchange can perfectly observe the quality of each project at a cost normalized to zero and decide whether to list it.[28] The exchange is a long-run player with a discount factor $\delta \in (0, 1)$. Issuers and investors are short-run players who only play once.[29] There are two types of cryptocurrency exchanges: honest exchanges and opportunistic exchanges. An honest exchange never lists a bad project. An opportunistic exchange acts strategically and may list bad projects to maximize its continuation payoff. The focus of the model is on analyzing the behavior and equilibrium properties of different types of opportunistic exchanges, i.e. first-tier and lower-tier exchanges. The reputation of an exchange is measured by a state variable q, which is the posterior probability that investors and issuers believe that the exchange is honest. q is updated by observing past realizations.

[27] Same equilibrium properties can be derived under the assumption that the good project never defaults.

[28] This is a standard assumption in the financial intermediation literature, which also makes sense for cryptocurrency markets. Cryptocurrency exchanges are assumed to have the expertise to observe the quality of projects through their information advantage, professional due diligence, etc.

[29] In cryptocurrency markets, investors may not be able to identify the bad-type exchanges because of crypto wash trading. Second-tier exchanges can manipulate their volume data to make them look as big as first-tier exchanges. Unsophisticated / inexperienced investors in this market can hardly tell the difference.

A (stationary) Markov strategy of the opportunistic exchange is a mapping:

$$x : [0,1] \to [0,1].$$

The opportunistic exchange lists bad projects with probability $x(q)$. Investors' and issuers' behavior are described by the Markov belief function:

$$m : [0,1] \to [0,1]$$

where $m(q)$ is the probability investors and issuers assign to a successful investment. Financing takes place if $m(q) \geq I$. $m(q)$ can be calculated using Bayes' rule:

$$m(q) = \frac{\gamma(1-p)}{\gamma + (1-\gamma)(1-q)x(q)}.$$

The issuer promises investors a repayment $D(q) \in [0,1]$ if the project succeeds. The (primary) market equilibrium is characterized by the zero profit condition:

$$m(q)D(q) = I.$$

Without loss of generality, assume that the exchange charges a listing fee $L(q)$ such that the issuer has zero profit. The zero-profit condition implies:

$$L(q) = \begin{cases} \dfrac{m(q)(1-D(q))}{\gamma + (1-\gamma)(1-q)x(q)}, & if \quad m(q) > I \\ 0, & if \quad m(q) \leq I \end{cases}$$

The players have some prior beliefs on the types of cryptocurrency exchanges and their beliefs are updated in a Bayesian fashion whenever possible.[30] At the end of each period, they observe one of the three possible outcomes: *Success (S)* when a good project is listed and succeeds, *Failure (F)* when a bad project is listed or a good project defaults,

[30] Figure 1.7 depicts the decision tree.

No financing (N) when no listing happens.[31] Following Bayes' rule:

$$\phi(q|S) \equiv q^S = q$$

$$\phi(q|F) \equiv q^F = \frac{q}{1 + (1-q)\frac{(1-\gamma)x(q)}{\gamma p}}$$

$$\phi(q|N) \equiv q^N = \frac{q}{1 - x(q)(1-q)}$$

Definition: A stationary Markov perfect equilibrium is a triple (x, m, ϕ) such that for all q:

(i) $x(q)$ maximize the profit of the cryptocurrency exchange

(ii) Players rationally update their beliefs based on Bayes' rule

(iii) $q^N = 0$ if $x(0) = 1$

The strategy x of the cryptocurrency exchange uniquely determines the equilibrium updating rule that investors and issuers use.

1.4.2 Revenue Source and Incentives to Cheat

Cryptocurrency exchanges have two income sources: revenue from mainstream coin trading and token listing and trading activities.[32] Exchanges receive commissions T_0 from trading in mainstream coins, t from trading in tokens, and L from listing tokens. In the baseline model, I assume that the trading commissions generated by all issued tokens for exchanges are proportionate to their listing commissions, so that they can be normalized to zero and combined with listing fees.[33] Listing fees are the major income source for lower-tier cryptocurrency exchanges. I thus assume that listing revenue is equal to the total revenue from tokens.

[31] When cryptocurrency exchanges choose to list a project, the listed token may give investors a positive return (i.e. when a good project succeeds) or zero return (i.e. when a bad project is listed or a good project fails). Cryptocurrency exchanges can also choose not to list the token after observing its quality.

[32] Mainstream coins are those of the largest market cap, which are not issued by entrepreneurs and listed by every exchange without charging any listing fee. Examples of mainstream coins include Bitcoin and Ethereum. Tokens are defined as the coins issued by entrepreneurs to finance their activities. For example, EOS, which was issued by block.one in 2018, has been the largest token so far. There are also many small tokens existing that have been widely studied empirically, see e.g. Howell et al. (2020).

[33] Compared to mainstream coins, trading volumes of issued tokens are much lower. Lower-tier exchanges typically do not receive large amounts of trading fees from issued tokens. Listing fees are thus good proxies for the future trading activities of issued tokens.

No Trading Revenue from Mainstream Coins

Consider the extreme case in the baseline that the revenue of cryptocurrency exchanges is only from listing. These cryptocurrency exchanges have no real fiat-crypto trading volume in mainstream coins such as Bitcoin and Ethereum. Many cryptocurrency exchanges operate in this fashion, and it is the typical business model of lower-tier exchanges. The value function of the opportunistic exchange is characterized by the Bellman equation:

$$
\begin{aligned}
V(q) = & \gamma \underbrace{[L(q) + \delta((1-p)V(q^S) + pV(q^F)]}_{\text{Profits from listing a good project}} \\
& + (1-\gamma)x(q) \quad \underbrace{[L(q) + \delta V(q^F)]}_{\text{Profits from listing a bad project}} \\
& + (1-\gamma)(1-x(q)) \quad \underbrace{\delta V(q^N)}_{\text{Profits from not listing a bad project}}
\end{aligned}
$$

To derive the equilibrium properties, note that x is an equilibrium strategy if and only if for any q and deviation x':

$$
\begin{aligned}
&(1-\gamma)x(q)[L(q) + \delta V(q^F)] + (1-\gamma)(1-x(q))\delta V(q^N) \geq \\
&(1-\gamma)x'(q)[L(q) + \delta V(q^F)] + (1-\gamma)(1-x'(q))\delta V(q^N)
\end{aligned}
$$

$$
\Rightarrow (x(q) - x'(q))(L(q) + \delta V(q^F)) \geq \delta(x(q) - x'(q))V(q^N)
$$

From this, Lemma 1 follows.

Lemma 1: $x(q) = 1$ is part of an equilibrium strategy if and only if

$$
L(q) + \delta V(q^F) \geq \delta V(q^N)
$$

$x(q) = 0$ is part of an equilibrium strategy if and only if

$$
L(q) + \delta V(q^F) \leq \delta V(q^N)
$$

$x(q) \in (0, 1)$ is part of an equilibrium strategy if and only if

$$
L(q) + \delta V(q^F) = \delta V(q^N).
$$

Opportunistic exchanges choose to cheat if and only if the sum of the listing revenue received in this period and the value of failure is more than the value of not listing any project. Opportunistic exchanges choose not to cheat if and only if the sum of the listing revenue received in this period and the value of failure is less than the value of not listing any project. There is a trade-off between increasing current revenue from listing and maintaining future revenue from not listing the bad project.

Proposition 1: At any equilibrium, the opportunistic cryptocurrency exchange's strategy consists in lying with positive probability for any q and lying for sure for q close to 1.[34]

Comments: This scenario illustrates the equilibrium results based on the business model of the typical lower-tier cryptocurrency exchanges. If there is no trading revenue from mainstream coins, then all income of the exchange comes from issued tokens. In this case, the cryptocurrency exchange only perform a certification role. When there is no other income source apart from its certification, the crytocurrency exchange would not have incentives to stay honest all the time. Lower-tier exchanges will never choose to be honest (i.e. $x(q) = 0$), as the gain from maintaining future revenue is not enough compared to the current revenue increase from listing fees. Without other income source, there is nothing that provides incentives for the exchange to stay honest and never list any bad projects. Moreover, when the reputation of lower-tier exchanges rises, it will even increase the possibility for them to list bad project, as their listing revenue this period tends to be larger compared to the discounted future revenue from not listing. In the case where there are no real trading activities in mainstream coins, reputation concern only from listing issued tokens is not sufficient for cryptocurrency exchanges to be self-disciplined. In consequence, plenty of lower-tier exchanges do not exist for a long period in the markets.[35]

With Trading Revenue from Mainstream Coins

Consider the case that the revenue of cryptocurrency exchanges is from trading and listing. These cryptocurrency exchanges have real fiat-crypto trading volume in main-

[34] See Appendix A.1 for the proof.

[35] According to Binance report in 2019, 16078 exchanges existed around the world. Many of them existed for a short period and died quickly.

stream coins such as Bitcoin and Ethereum. This is the typical business model of first-tier exchanges. Suppose that trading revenue is lost forever when $q < \bar{q}$.[36] In reality, it may happen in different cases: (1) Regulators will withdraw its license, (2) Brokers will cease its partnership, (3) investors choose not to trade mainstream coins through the cryptocurrency exchange. Formally, the trading revenue from mainstream coins is denoted as $T_0 1_{\{q>\bar{q}\}}$, with $T_0 > 0$.

The value function of opportunistic exchange is characterized by a Bellman equation:

$$\begin{aligned}
W(q) \equiv & T_0 1_{\{q\geq\bar{q}\}} + V(q) \\
= & T_0 1_{\{q\geq\bar{q}\}} + \gamma \underbrace{[L(q) + \delta((1-p)V(q^S) + pV(q^F)]}_{\text{Profits from listing a good project}} \\
& + (1-\gamma)x(q) \quad \underbrace{[L(q) + \delta V(q^F)]}_{\text{Profits from listing a bad project}} \\
& + (1-\gamma)(1-x(q)) \quad \underbrace{\delta V(q^N)}_{\text{Profits from not listing a bad project}}
\end{aligned}$$

Consider the case that q is equal to $\bar{q}$, opportunistic exchange has incentives to be self-disciplined. Same as Mathis et al. (2009), we focus on the equilibria where the cryptocurrency exchange is active, that is, $V(q) > 0$ for all $q > 0$.

Proposition 2: If $T_0 > \frac{\gamma L(\bar{q})}{1-\delta}$, there exists a unique equilibrium such that the opportunistic cryptocurrency exchange always tells the truth: $x^*(\bar{q}) = 0$. If $\bar{q}$ is large enough, exchanges with large trading revenue will seldom choose to cheat. In the extreme case when $\bar{q}$ is 1, exchanges with large trading revenue will never cheat.[37]

Comments: This scenario illustrates the incentive constraints of the no-cheating equilibrium results based on the business model of the typical first-tier cryptocurrency exchanges. If there is trading revenue from mainstream coins, the cryptocurrency exchanges generate income from two sources: trading and listing. The certification role will be disciplined by the mainstream trading activities. Compared to the case in Proposition 1, there is an additional revenue source affecting the trade-off between increasing current revenue and maintaining future revenue, i.e., T_0. Listing a token may lead to a risk of losing future trading revenue. Thus, trading revenue T_0 contributes to truthful

[36] $\bar{q}$ is a constant perceived by outsiders, e.g. regulators, brokers, investors, etc.

[37] See Appendix A.1 for a proof.

listing decisions. When a large enough fraction of the cryptocurrency exchange income comes from trading activities instead of listing activities, opportunistic exchanges will always have the incentive to stay honest and never list bad projects. Under the incentive constraint, reputational concerna are sufficient to discipline cryptocurrency exchanges. Cryptocurrency exchanges whose major revenue comes from trading business would always be self-disciplined in certification. Moreover, the cryptocurrency exchanges with large trading revenue may choose to list fewer tokens in order to maintain a high reputation and trading revenue from mainstream coins.[38]

1.4.3 First-mover Advantages

The above propositions provide a theoretical framework to understand why exchange characteristics are associated with the quality of listed tokens. In addition to asset pricing implications, the income-driven market segmentation in the cryptocurrency industry has broader implications for its market structure and industry organization. The empirical findings on exchange characteristics and token performance also suggest the existence of market segmentation and first-mover advantages in the cryptocurrency exchange industry.

The model can be extended to illustrate first-mover advantages in the cryptocurrency exchange industry. Suppose that at $t = 0$, regulator/broker/investors randomly choose an exchange to trade mainstream coins. The first-mover exchange then becomes a first-tier exchange. If the first-tier exchange cheats, it loses its trading revenue and becomes lower-tier. One of its competitors (i.e. lower-tier exchange) is then randomly chosen to support trading activities and become first-tier. However, in equilibrium, this never happens. In equilibrium, lower-tier exchanges cannot compete with first-tier exchanges.A feedback loop then creates a barrier to entry in the first-tier segment.

There is a vicious circle for lower-tier exchanges as second-movers, who are stuck in a bad equilibrium. Lower-tier exchanges have a lower reputation than first-tier exchanges thus no one uses lower-tier exchanges to trade mainstream coins. First-tier exchanges have more trading revenue than lower-tier exchanges. Lower-tier exchanges cannot survive through their trading revenue, so they have to rely on listing revenue as their income source. In order to be profitable, lower-tier exchanges lower their listing fees to attract

[38]For example, Coinbase only listed 43 coins in Feb 2021.

more lower-quality tokens. Lower-tier exchanges list more low-quality tokens and the reputation of lower-tier exchanges further decreases.

1.5 Discussion

1.5.1 Competition Among First-mover Exchanges

Why do incumbents have market power? If trading is a homogeneous product and first-tier exchanges compete with each other with no collusion, trading profits should be driven down to zero. However, they make significant profits in trading markets. In addition, trading profits are necessary for first-tier exchanges to care about reputation. Why do first-tier exchanges make large profits in trading market? There are three factors: investors' preferences, product differentiation, and switching cost. First, investors have preferences for some characteristics of exchange products (e.g. leverage, staking, liquidity, token diversity). Second, exchanges provide differentiated products, so they do not compete directly with each other (e.g. target different geography and types of customers, provide different products). Third, even if trading products are homogeneous, switching costs can explain the trading fee differences.

It is also interesting to explore whether trading profits of exchanges are due to collusion, namely, exchanges collude with each other in setting trading fees. The non cooperative equilibrium in an oligopoly with switching costs may be the same as the collusive outcome in an otherwise identical market without switching costs (Klemperer (1987)).

1.5.2 Fees for Investors

Figure 1.8 shows trading fees, funding fees, and discounts of major cryptocurrency exchanges in 2020. Trading fees are charged on both fiat-crypto and crypto-crypto trades. There are also deposit/withdrawal fees, while deposit fees are less common than withdrawal fees. The third major fees are interest/borrowing/liquidation fees. Some exchanges offer crypto margin trading. If the trade goes upside down and the position is liquidated, investors may be charged an additional fee. Discounts are also typically applied. For example, there are market maker and volume discounts. Moreover, exchange token discounts are offered to users who purchase an exchange's own token. US-regulated

KYC exchanges (e.g., Gemini and Coinbase) charge higher fees than other exchanges, reflecting a regulatory premium. While listing fees are not public information, anecdotal evidence suggests that exchanges of different size and popularity charge different listing fees.[39]

1.6 Conclusion

This paper studies cryptocurrency exchange industry dynamics and listed token performance. Cryptocurrency exchanges play the dual roles of traditional exchanges and underwriters. The two different roles interact, creating two alternative business models. Trading revenue provides incentives for cryptocurrency exchanges to be self-disciplined in listing.

This paper shows evidence of cryptocurrency exchange heterogeneity and market segmentation. I show that tokens listed in exchanges with significant trading revenues perform better and that token returns are predictable by exchange token characteristics, with more pronounced effects among exchanges with significant trading revenues. I develop a stylized reputation model of the interaction between trading and listing. The model shows how the existence of different business models in the cryptocurrency exchange industry can explain the correlation between token performance and exchange characteristics.

[39] The top tier exchanges with the largest trading volume charge between 1 to 2.5 million USD for a token listing. Medium-sized second-tier exchanges typically charge from 10 to 50 BTC. The prices that lower-tier exchanges charge can be as low as 0.5 to 1 BTC.

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Figures and Tables

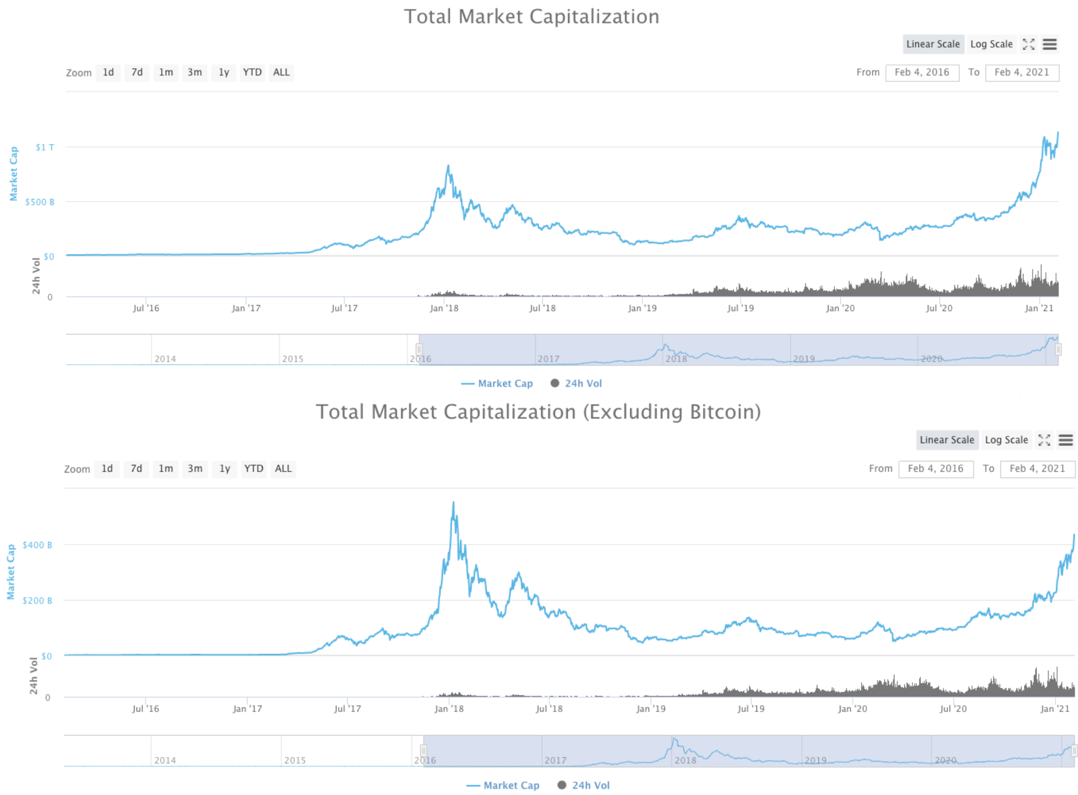

Figure 1.1: Total Market Capitalization of Bitcoins and Altcoins

Notes: This figure reports the total market capitalization of cryptocurrency markets with and without Bitcoin from 2015 to 2021.

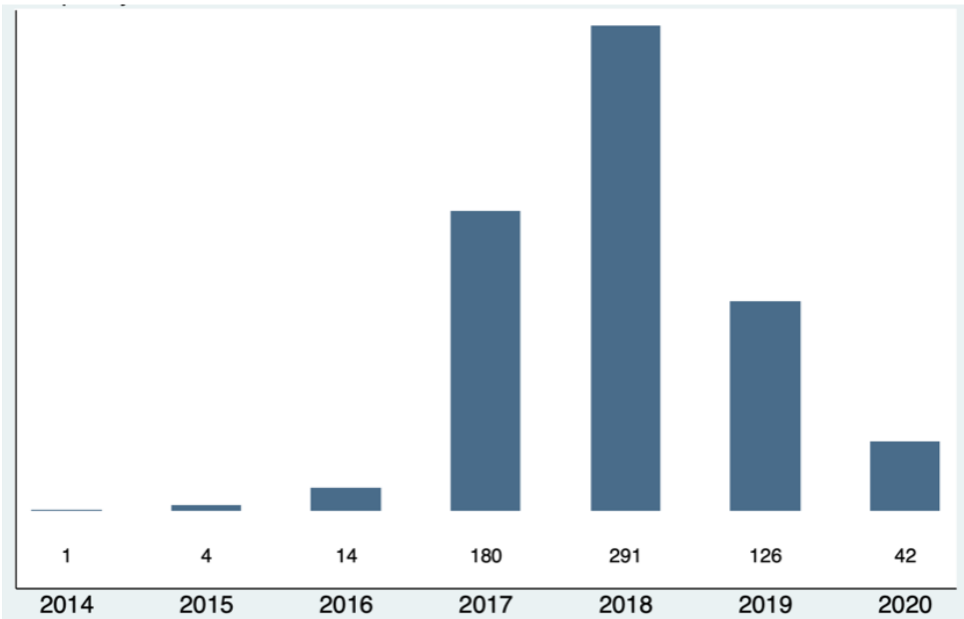

Figure 1.2: Summary Statistics: Listed Tokens by Year

Notes: This figure reports the number of tokens listed by year from 2014 to 2020.

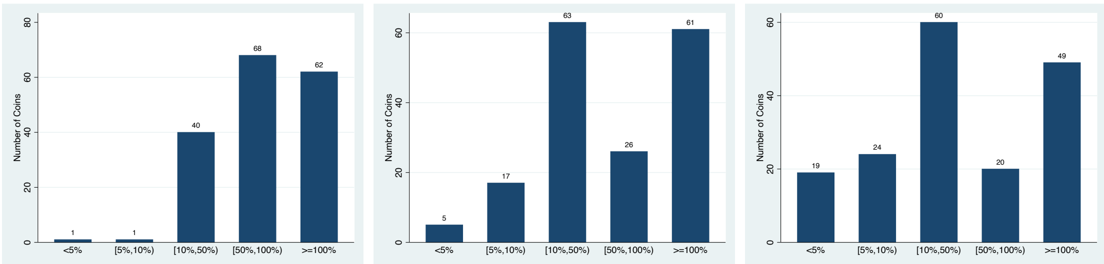

Figure 1.3: Price Ratio of Coins on First-tier Exchanges (1m, 6m, 1yr)

Notes: This figure reports the price ratio of tokens listed by first-tier exchanges in 1,6, and 12 months after the initial listing. Failure rate is calculated based on the changes in price of the tokens.

$$Ratio = \frac{X_t}{X_0}$$

where X_0 denotes the token price at the initial listing, X_t denotes the token price t months after initial listing.

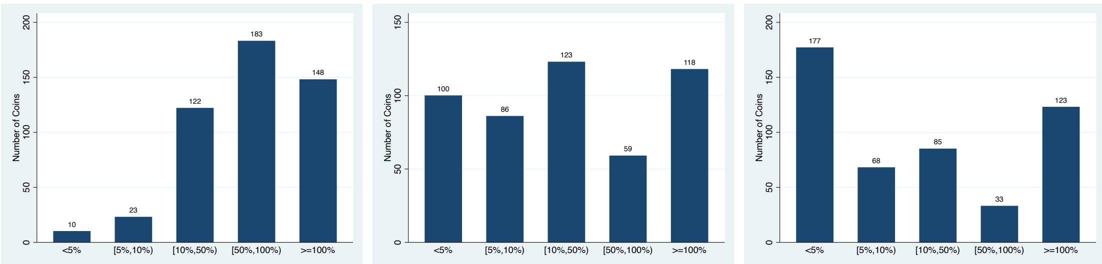

Figure 1.4: Price Ratio of Coins on Second-tier Exchanges (1m, 6m, 1yr)

Notes: This figure reports the price ratio of tokens listed by second-tier exchanges in 1,6, and 12 months after the initial listing. Failure rate is calculated based on the changes in price of the tokens.

$$Ratio = \frac{X_t}{X_0}$$

where X_0 denotes the token price at the initial listing, X_t denotes the token price t months after initial listing.

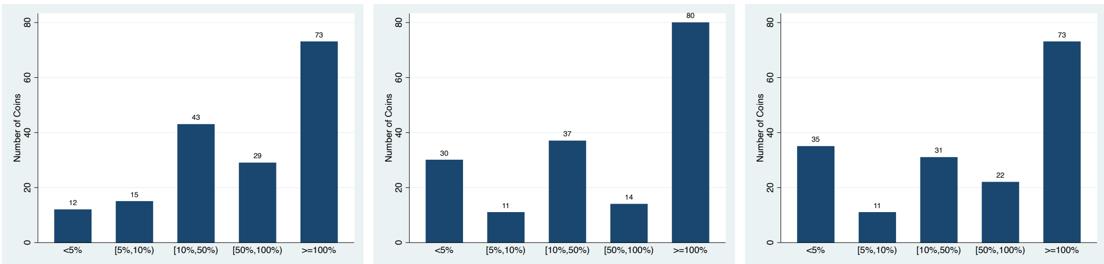

Figure 1.5: Volume Ratio of Coins on First-tier Exchanges (1m, 6m, 1yr)

Notes: This figure reports the volume ratio of tokens listed by first-tier exchanges in 1,6, and 12 months after the initial listing. Failure rate is calculated based on the changes in trading volume of the tokens.

$$Ratio = \frac{X_t}{X_0}$$

where X_0 denotes the token trading volume at the initial listing, X_t denotes the token trading volume t months after initial listing.

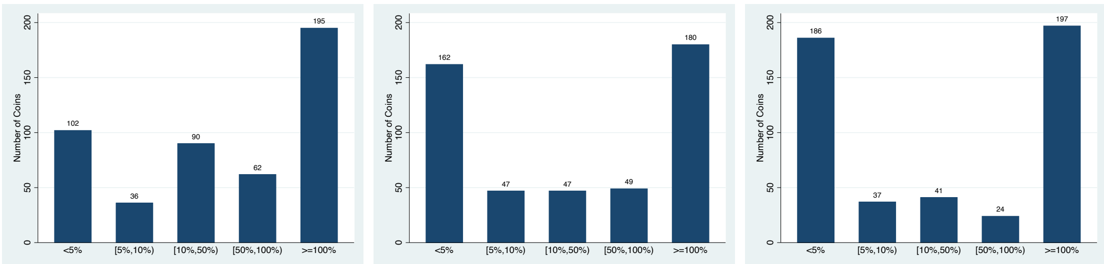

Figure 1.6: Volume Ratio of Coins on Second-tier Exchanges (1m, 6m, 1yr)

Notes: This figure reports the volume ratio of tokens listed by second-tier exchanges in 1,6, and 12 months after the initial listing. Failure rate is calculated based on the changes in trading volume of the tokens.

$$Ratio = \frac{X_t}{X_0}$$

where X_0 denotes the token trading volume at the initial listing, X_t denotes the token trading volume t months after initial listing.

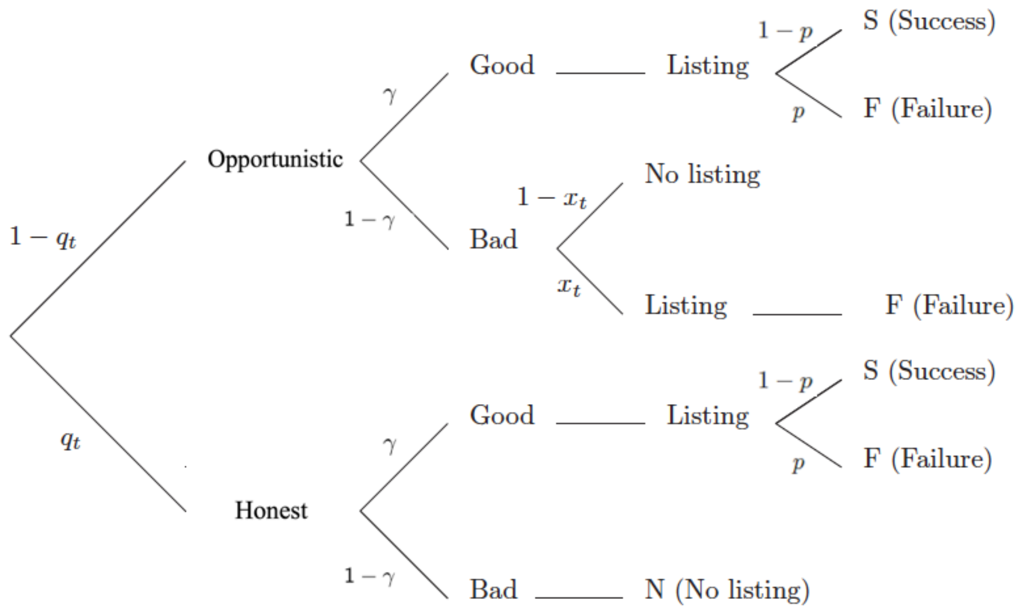

Figure 1.7: Decision Tree of Cryptocurrency Exchange Listing

Notes: This figure reports the decision tree of cryptocurrency exchange listing.

Exchange	Trading Fees			Funding Fees		Discounts	
	Maker	Taker	Spread	Deposits	Withdrawals	Exchange Token Discount	Volume Discount
Bibox	0.1%	0.1%	No	No	Yes	Yes	No
Binance	0.1%	0.1%	No	No	Yes	Yes	Yes
Bitfinex	0.1%	0.2%	No	Yes (< $1k)	Yes	No	Yes
Bitsane	0.1%	0.2%	No	Yes	Yes	No	Yes
Bitstamp	0.25%	0.25%	No	No	No	No	Yes
Bittrex	0.25%	0.25%	No	No	No	No	No
BTCMarkets	0.22%-0.85%	0.22%-0.85%	No	No	Yes (AUD free)	No	Yes
CEX.IO	0.16%	0.25%	No	No	Yes	No	Yes
Coinbase	N/A	1.49% or fixed fee	~0.50% fiat 1.00% crypto	No	No	No	Yes
Coinbase Pro	0.15%	0.25%	No	No	No	No	Yes
Coinspot	0.1%	0.1%	No	Yes	No	No	No
Coss	0.14%	0.20%	No	Yes	Yes	Yes	Yes
Cryptopia	0.2%	0.2%	No	No	No	No	No
Gate.io	0.2%	0.2%	No	No	Yes	No	Yes
Gemini	1.00%	1.00%	No	No	No	No	Yes
HitBTC	0.1%	0.2%	No	No	No	No	No
Huboi	0.2%	0.2%	No	No	No	Yes	Yes
IDEX	0.1%	0.2%	No	No	No	No	No
Kraken	0.16%	0.26%	No	No	No	No	Yes
Kucoin	0.1%	0.1%	No	No	No	No	Yes
Livecoin	0.18%	0.18%	No	Yes	Yes	No	Yes
Liquid	0.1%	0.1%	No	No	Yes	Yes	Yes
Poloniex	0.08%	0.20%	No	No	Yes	No	Yes
Shakepay	0.75%	0.75%	No	No	Yes - $2.99-$3.99	No	No
Uphold	0.65% - 1.95%	0.65% - 1.95%	No	No	Yes	No	No

Figure 1.8: Trading Fees in Cryptocurrency Exchanges

Notes: This figure reports the trading fee charged in different cryptocurrency exchanges.

Table 1.1: Summary Statistics: Distributions of Listed Token Performance

	mean	sd	min	p25	p50	p75	p90	p95	max	count
Ret1	-0.02	0.37	-3.25	-0.13	-0.02	0.09	0.29	0.45	2.39	664
Ret3	-0.07	0.66	-11.87	-0.27	-0.06	0.13	0.47	0.72	2.03	664
Ret7	-0.13	0.67	-5.89	-0.39	-0.11	0.14	0.52	0.80	3.40	664
Ret14	-0.20	0.72	-5.17	-0.59	-0.21	0.14	0.67	0.94	2.73	664
Ret21	-0.26	0.94	-9.20	-0.69	-0.26	0.16	0.72	1.10	4.84	662
Ret30	-0.34	1.05	-9.20	-0.82	-0.34	0.15	0.77	1.22	4.97	662
Ret60	-0.46	1.20	-5.96	-1.13	-0.50	0.17	0.89	1.50	5.59	659
Ret90	-0.60	1.34	-6.66	-1.39	-0.63	0.05	1.02	1.70	6.02	652
Ret180	-1.05	1.72	-6.47	-2.05	-1.22	-0.05	1.10	1.93	9.09	635
Ret360	-1.69	1.93	-7.64	-2.84	-1.77	-0.61	0.79	1.41	6.52	593
Ret720	-2.68	2.18	-9.62	-4.02	-2.82	-1.35	-0.14	0.96	5.82	434
AdjRet1	-0.02	0.36	-3.29	-0.13	-0.02	0.09	0.28	0.46	2.39	664
AdjRet3	-0.07	0.66	-11.93	-0.26	-0.06	0.11	0.42	0.74	2.03	664
AdjRet7	-0.13	0.66	-5.89	-0.37	-0.11	0.11	0.51	0.78	3.47	664
AdjRet14	-0.21	0.71	-5.16	-0.57	-0.22	0.15	0.57	0.90	2.57	664
AdjRet21	-0.28	0.92	-9.13	-0.69	-0.26	0.10	0.67	1.02	4.75	662
AdjRet30	-0.38	1.02	-9.14	-0.81	-0.37	0.07	0.74	1.15	4.75	662
AdjRet60	-0.55	1.15	-6.32	-1.15	-0.59	0.06	0.82	1.29	5.11	659
AdjRet90	-0.69	1.24	-6.81	-1.33	-0.68	0.02	0.77	1.36	5.12	652
AdjRet180	-1.10	1.51	-6.32	-1.90	-1.11	-0.23	0.69	1.24	7.25	635
AdjRet360	-1.74	1.63	-7.95	-2.61	-1.66	-0.74	0.04	0.71	4.78	593
AdjRet720	-2.98	1.89	-9	-4.18	-2.99	-1.83	-0.80	0.07	4.15	434

Notes: This table reports the summary statistics and distribution of short-term and log-term log return of listed token return. Ret_i stands for short-term log return and long-term log return 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing. $AdjRet_i = Ret_i - Ret_{BTC}$ is the adjusted short-term and long-term report, i.e. raw performance subtracted by the corresponding performance of Bitcoin.

Table 1.2: Token Performance Across Exchanges: Web Traffic Measure

	Ret1	Ret3	Ret7	Ret14	Ret21	Ret30
First	-0.0354	0.0417	0.0731	0.0946*	0.0156***	0.0666***
	(-0.37)	(0.58)	(1.18)	(1.74)	(2.74)	(2.91)
# observations	664	664	664	664	662	662
	Ret60	Ret90	Ret180	Ret360	Ret720	
First	0.0306***	0.0201***	0.0802***	0.0429***	0.0648***	
	(3.78)	(4.56)	(5.33)	(5.98)	(6.66)	
# observations	659	652	635	593	434	
	AdjRet1	AdjRet3	AdjRet7	AdjRet14	AdjRet21	AdjRet30
First	-0.0378	0.0433	0.0870	0.0624	0.0625**	0.0579***
	(-0.29)	(0.74)	(1.19)	(1.57)	(2.55)	(2.68)
# observations	664	664	664	664	662	662
	AdjRet60	AdjRet90	AdjRet180	AdjRet360	AdjRet720	
First	0.0201***	0.0456***	0.0847***	0.0421***	0.0787***	
	(2.93)	(3.67)	(5.24)	(6.90)	(6.40)	
# observations	659	652	635	593	434	

Notes: This table reports the difference of token performance across the two types of exchanges (i.e. first-tier exchange and second-tier exchanges) based on web traffic measure. Specifically, this table compares the performance of tokens that are listed by first-tier and second-tier exchanges 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Ret_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and Ret_i stands for short-term log return and long-term log return.

$$AdjRet_i = \alpha + \beta First_i + \epsilon_i$$

where $AdjRet_i = Ret_i - Ret_{BTC}$.
The first two rows report the results of raw performance, while the last two rows report the results of the adjusted performance, i.e. raw performance subtracted by the corresponding performance of Bitcoin.

Table 1.3: Token Marketcap Across Exchanges: Web Traffic Measure

	Cap1	Cap3	Cap7	Cap14	Cap21	Cap30
$First$	1.733***	1.890***	2.031***	1.746***	1.679***	1.627***
	(4.68)	(6.37)	(8.39)	(8.88)	(9.51)	(9.77)
# observations	111	156	227	318	379	418
	Cap60	Cap90	Cap180	Cap360	Cap720	
$First$	1.850***	1.956***	2.200***	2.434***	2.598***	
	(11.67)	(12.11)	(12.57)	(14.27)	(12.49)	
# observations	485	508	523	522	422	
	AdjCap1	AdjCap3	AdjCap7	AdjCap14	AdjCap21	AdjCap30
$First$	2.268***	2.235***	2.243***	1.903***	1.723***	1.606***
	(5.81)	(6.77)	(8.47)	(8.81)	(8.82)	(8.64)
# observations	111	156	227	318	379	418
	AdjCap60	AdjCap90	AdjCap180	AdjCap360	AdjCap720	
$First$	1.685***	1.849***	1.970***	2.411***	2.630***	
	(9.74)	(11.16)	(10.82)	(12.28)	(12.33)	
# observations	485	508	523	522	422	

Notes: This table reports the difference of token performance across the two types of exchanges (i.e. first-tier exchange and second-tier exchanges) based on web traffic measure. Specifically, this table compares the performance of tokens that are listed by first-tier and second-tier exchanges 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Cap_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and Cap_i stands for log market capitalization.

$$AdjCap_i = \alpha + \beta First_i + \epsilon_i$$

where $AdjCap_i = Cap_i - Cap_{BTC}$.
The first two rows report the results of raw performance, while the last two rows report the results of the adjusted performance, i.e. raw performance subtracted by the corresponding performance of Bitcoin.

Table 1.4: Token Cumulative Trading Volume Across Exchanges: Web Traffic Measure

	Vol1	Vol3	Vol7	Vol14	Vol21	Vol30
$First$	2.132***	2.102***	2.093***	2.110***	2.188***	2.221***
	(8.89)	(9.57)	(9.73)	(10.36)	(10.95)	(11.20)
# observations	658	660	660	662	661	661
	Vol60	Vol90	Vol180	Vol360	Vol720	
$First$	2.294***	2.357***	2.563***	2.525***	2.390***	
	(11.98)	(12.55)	(14.01)	(14.73)	(11.85)	
# observations	658	651	634	592	434	
	AdjVol1	AdjVol3	AdjVol7	AdjVol14	AdjVol21	AdjVol30
$First$	2.348***	2.318***	2.317***	2.319***	2.373***	2.390***
	(10.34)	(11.23)	(11.43)	(12.05)	(12.53)	(12.69)
# observations	658	660	660	662	661	661
	AdjVol60	AdjVol90	AdjVol180	AdjVol360	AdjVol720	
$First$	2.397***	2.413***	2.548***	2.627***	2.599***	
	(13.20)	(13.58)	(14.51)	(14.47)	(12.22)	
# observations	658	651	634	592	434	

Notes: This table reports the difference of token performance across the two types of exchanges (i.e. first-tier exchange and second-tier exchanges) based on web traffic measure. Specifically, this table compares the performance of tokens that are listed by first-tier and second-tier exchanges 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Vol_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and Vol_i stands for log cumulative trading volume.

$$AdjVol_i = \alpha + \beta First_i + \epsilon_i$$

where $AdjVol_i = Vol_i - Vol_{BTC}$.
The first two rows report the results of raw performance, while the last two rows report the results of the adjusted performance, i.e. raw performance subtracted by the corresponding performance of Bitcoin.

Table 1.5: Token Volatility Across Exchanges: Web Traffic Measure

	SD30	SD60	SD90	SD180	SD360	SD720
$First$	-2.166	-1.898	-1.828	-3.969	-3.493	-2.486
	(-0.05)	(-0.06)	(-0.07)	(-0.21)	(-0.26)	(-0.26)
# observations	662	659	652	635	593	434
	AdjSD30	AdjSD60	AdjSD90	AdjSD180	AdjSD360	AdjSD720
$First$	-2.167	-1.899	-1.831	-3.972	-3.497	-2.490
	(-0.05)	(-0.06)	(-0.07)	(-0.21)	(-0.26)	(-0.26)
# observations	662	659	652	635	593	434

Notes: This table reports the difference of token volatility across the two types of exchanges (i.e. first-tier exchange and second-tier exchanges) based on web traffic measure. Specifically, this table compares the volatility of tokens that are listed by first-tier and second-tier exchanges 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$SD_i = \alpha + \beta First_i + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and SD_i stands for the volatity of token return.

$$AdjSD_i = \alpha + \beta First_i + \epsilon_i$$

where $AdjSD_i = SD_i - SD_{BTC}$.
The first two rows report the results of raw volatility, while the last two rows report the results of the adjusted volatility, i.e. raw volatility subtracted by the corresponding volatility of Bitcoin.

Table 1.6: Token Performance Across Exchanges: Exchange Token

	Ret1	Ret3	Ret7	Ret14	Ret21	Ret30
$\text{Ret}_{ex,t-30\to t-1}$	0.0232***	0.0173**	0.0243**	0.0351**	0.0695***	0.0623**
	(4.75)	(2.32)	(2.04)	(2.54)	(2.71)	(2.34)
R^2	0.169	0.118	0.0839	0.119	0.0862	0.0890
# observations	236	236	236	236	234	234
	Ret60	Ret90	Ret180	Ret360	Ret720	
$\text{Ret}_{ex,t-30\to t-1}$	0.256***	0.110**	0.112	0.0137	0.00487	
	(4.42)	(2.54)	(1.30)	(0.69)	(0.45)	
R^2	0.149	0.280	0.0987	0.0711	0.0636	
# observations	233	230	226	217	141	
	AdjRet1	AdjRet3	AdjRet7	AdjRet14	AdjRet21	AdjRet30
$\text{Ret}_{ex,t-30\to t-1}$	0.0236***	0.0200***	0.0243**	0.0341**	0.0544**	0.0327
	(4.84)	(2.70)	(2.08)	(2.50)	(2.13)	(1.25)
R^2	0.165	0.126	0.0789	0.112	0.0722	0.0778
# observations	236	236	236	236	234	234
	AdjRet60	AdjRet90	AdjRet180	AdjRet360	AdjRet720	
$\text{Ret}_{ex,t-30\to t-1}$	0.241***	0.115***	0.112	0.0373*	0.0135	
	(4.28)	(2.73)	(1.31)	(1.81)	(1.18)	
R^2	0.141	0.295	0.0839	0.160	0.138	
# observations	233	230	226	217	141	

Notes: This table reports the effects of past exchange token return on the return of token listed on the exchange based on exchange token measure. Specifically, this table uses the past 1-month cryptocurrency exchange token return as a predictor to predict the listed token return 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Ret_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $Ret_{exchange,t-30\to t-1}$ is past 1-month cryptocurrency exchange token return, Ret_i stands for the short-term and long-term log return of the token listed on the exchange, and $\gamma_{exchange}$ is the exchange fixed effects.

$$AdjRet_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \epsilon_i$$

where $AdjRet_i = Ret_i - Ret_{BTC}$.
The first two rows report the results of raw return, while the last two rows report the results of the adjusted return, i.e. raw return subtracted by the corresponding return of Bitcoin.

Table 1.7: Token Volatility Across Exchanges: Exchange Token

	SD30	SD60	SD90	SD180	SD360	SD720
$\text{Ret}_{ex,t-30\rightarrow t-1}$	0.00215	0.00287	0.00167	0.00390	0.00211	0.00217
	(0.13)	(0.09)	(0.06)	(0.00)	(0.00)	(0.00)
# observations	234	233	230	226	217	141
	AdjSD30	AdjSD60	AdjSD90	AdjSD180	AdjSD360	AdjSD720
$\text{Ret}_{ex,t-30\rightarrow t-1}$	0.00235	0.00284	0.00144	0.00369	0.00193	0.00210
	(0.14)	(0.09)	(0.06)	(0.00)	(0.00)	(0.00)
# observations	234	233	230	226	217	141

Notes: This table reports the effects of past exchange token return on the volatility of token listed on the exchange based on exchange token measure. Specifically, this table uses the past 1-month cryptocurrency exchange token return as a predictor to predict the listed token volatility 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$SD_i = \alpha + \beta Ret_{exchange,t-30\rightarrow t-1} + \gamma_{exchange} + \epsilon_i$$

where $Ret_{exchange,t-30\rightarrow t-1}$ is past 1-month cryptocurrency exchange token return, SD_i stands for the volatility of the token listed on the exchange, and $\gamma_{exchange}$ is the exchange fixed effects.

$$AdjSD_i = \alpha + \beta Ret_{exchange,t-30\rightarrow t-1} + \gamma_{exchange} + \epsilon_i$$

where $AdjSD_i = SD_i - SD_{BTC}$.
The first two rows report the results of raw volatility, while the last two rows report the results of the adjusted volatility, i.e. raw volatility subtracted by the corresponding volatility of Bitcoin.

Table 1.8: Token Performance and Exchange Token Characteristics

	(1) *Ret*	(2) *Ret*	(3) *Ret*	(4) *AdjRet*	(5) *AdjRet*	(6) *AdjRet*
$Ret_{exchange}$	0.0552***			0.0127***		
	(5.42)			(4.84)		
$\Delta MarketCap$		0.000760***			0.000472***	
		(12.91)			(7.28)	
$\Delta Volume$			0.000169***			0.000242***
			(6.88)			(7.02)
# observations	293132	210965	245779	293132	210965	245779

Notes: This table reports the effects of past exchange token performance on the return of token listed on the exchange using real-time daily return. Exchange tokens' characteristics are used as proxies, including past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change.

$$Ret_{i,t} = \alpha + \beta X_{i,t-14 \to t-1} + \gamma_i + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return of the listed token, $X_{i,t-14 \to t-1}$ stands for past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change, and γ_i is the token fixed effects.

$$AdjRet_{i,t} = \alpha + \beta X_{i,t-14 \to t-1} + \gamma_i + \epsilon_{i,t}$$

where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ stands for the daily return of Bitcoin. Column (1)-(3) shows the results of token return, while Column (4)-(6) exhibits the results of adjusted token return.

Table 1.9: Token Performance and Exchange Token Characteristics: Heterogeneity

	(1) *Ret*	(2) *Ret*	(3) *Ret*	(4) *AdjRet*	(5) *AdjRet*	(6) *AdjRet*
$Ret_{exchange} \times First$	0.038**			0.141***		
	(1.99)			(6.66)		
$Ret_{exchange}$	0.0425***			0.0364***		
	(3.22)			(2.60)		
$\Delta MarketCap \times First$		0.000513***			0.000575***	
		(3.93)			(4.38)	
$\Delta MarketCap$		0.000382***			0.0000584	
		(3.39)			(0.56)	
$\Delta Volume \times First$			0.000444***			0.000835***
			(10.05)			(15.71)
$\Delta Volume$			0.0000297			-0.0000193
			(1.19)			(-0.76)
$First$	0.00422***	0.00330***	0.00423***	0.0046***	0.00395***	0.00398***
	(7.55)	(5.62)	(7.52)	(7.98)	(6.96)	(8.38)
# observations	293132	210965	245779	293132	210965	245779

Notes: This table reports the heterogeneous effects of past exchange token performance on the return of token listed on the exchange using real-time daily return. Exchange tokens' characteristics are used as proxies, including past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change.

$$Ret_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return of the listed token, $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, $X_{i,t-14\to t-1}$ stands for past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change, and γ_i is the token fixed effects.

$$AdjRet_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \epsilon_{i,t}$$

where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ stands for the daily return of Bitcoin. Column (1)-(3) shows the results of token return, while Column (4)-(6) exhibits the results of adjusted token return.

Chapter 2

Distrust and Cryptocurrency

Bitcoin trading is more active in countries where people express more distrust in others. This paper argues that distrust serves as a fundamental for cryptocurrency valuation by exploring price differences in panel data. We proxy Bitcoin demand with transitory price deviations—Bitcoin prices in a local currency, converted into dollars, relative to the average worldwide dollar Bitcoin prices. A simple portfolio choice model elucidates several predictions we find in the data. Price deviations rise when 1) perceptions of institutional failures grow, 2) crypto-trading frictions increase, and 3) cryptocurrency prices rally. Consistent with the model's predictions, distrust explains price response heterogeneity: investors in low-trust countries demand more Bitcoins and drive up its price relative to the world dollar price when local institutional quality deteriorates, arbitrage frictions intensify, and risk appetite rises.

JEL-Classification: G11, G12, G15.

Keywords: Cryptocurrency, Bitcoin, Trust, Limits of Arbitrage, Price Deviations, Institutional Failures

"Recent bitcoin trends highlight the local impact of global developments. In places where distrust of banks historically runs high, many households now consider bitcoin among the assets they trust more than the local fiat currency. ... Lebanon, Ecuador and Venezuela are also on the brink. Bitcoiners in Lebanon often focus on savings because they, like Latin Americans, share a distrust in banks."

— Yahoo Finance 9 Apr 2020

2.1 Introduction

It has been widely reported that the fragility of local institutions has driven people to demand alternative assets outside their countries. As many have argued, Bitcoin is perceived as a safe-haven asset, much like gold, that provides algorithmic trust governed by decentralized blockchains and satisfies investors' safety needs. Does distrust drive the demand for cryptocurrency? In this paper, we measure trust by the trust measure from the Global Preference Survey, which captures the general trust level of different countries.[1] We find that distrust in local institutions drives the demand for cryptocurrencies and explains time-varying price deviations. Our paper shows that cryptocurrencies are more valuable to investors from countries with low trust.

We study the Bitcoin prices expressed in different currencies to identify the sources of Bitcoin demand. We define the price deviation as the ratio of the Bitcoin price in a local currency, converted into dollars at the real-time exchange rate, to the average worldwide dollar price of Bitcoin. Price deviations frequently appear in many countries and can persist. For example, In October 2017, Bitcoin's price in Korean Won was similar to — even modestly lower than — the US Bitcoin price. Three months later, in early January 2018, the Korean price rallied to 37.5% higher than the US price. The violation of the law of one price in Bitcoin trading is crucial. If arbitrage works perfectly, prices will not differ even if the demand for Bitcoin varies by location. Our paper studies the driving forces in price deviations and argues that distrust plays a central role in explaining cross-country Bitcoin demand.

[1] See Falk et al. (2018) for a more detailed description of the Global Preference Survey.

First, we incorporate trust into a simple portfolio choice model and derive the closed-form solution for price deviation. Distrust makes domestic investment less attractive and tilts the portfolio toward Bitcoin. Our model predicts that the price deviation rises when institutional quality deteriorates, arbitrage friction increases, and risk appetite increases. Distrust amplifies Bitcoin demand; thus, the price deviation would react more in low-trust countries than in high-trust countries to the same shock. For example, facing the same political scandal, investors with lower trust perceive a higher risk in their domestic investment and shift to Bitcoin more aggressively, thus driving local Bitcoin prices higher relative to the international market.

Then, we test the model predictions in Bitcoin trading data from 2015 to 2020. We proxy domestic institutional failures with Google trend indices of the keywords "Conflict," "Crisis," "Instability," and "Scandal." One core finding is that deterioration of institutional quality drives local Bitcoin prices up: One standard deviation increase in occurrences of the word "Conflict" corresponds to a 1.74% increase in the price difference; similarly, increases of 0.78% are seen for "Crisis," 1.44% for "Instability," and 1.10% for "Scandal." In parallel, we find that trading volume surges concurrently, and people show more interest in Bitcoin on Google during periods with institutional failures. Consistent with the model prediction, the price deviation response mainly concentrates in low-trust countries and diminishes or even disappears in high-trust countries.

Another way to measure the frequency of price deviations is by return co-movement. Co-movement should be perfect if prices are the same in different countries. We quantify the arbitrage frictions with the return asynchronization, deviations from perfect return co-movement, which is formally defined as one hundred per cent minus the correlation between returns of Bitcoins traded in domestic currency and dollar-priced Bitcoins. The model predicts that local Bitcoin prices would rise when arbitrage becomes more difficult, and price reactions are more massive in low-trust countries. In the data, we find the price deviation increases by 8.5 basis points (bps) on average when return asynchronization goes up by 1%. The numbers are 4.3 bps in high-trust countries, 7.6 bps in medium-trust countries, and 13.9 bps in low-trust countries. In reaction to the same unit change in friction, Bitcoin prices rise three times more in low-trust countries than in high-trust countries.

Furthermore, we measure risk appetite in two ways — Bitcoin past returns to proxy global risk preference of crypto-investors and local stock market returns to proxy domestic investors' risk appetite. We find that Bitcoin is sold 1.2 bps higher on the domestic exchange when US Bitcoin rallied by 1% during the past eight weeks; similarly, it is sold 2.4 bps higher when the domestic stock market rose by 1% over the past eight weeks. Consistent with our prediction, low-trust countries contribute the most: A 1% past Bitcoin return increase corresponds to 1.7 bps increase, and a 1% past stock return increase corresponds to 8.0 bps increase in price deviation, respectively.

Price deviations can reflect the underlying cross-country Bitcoin demand only if the law of one price fails. We empirically give content to the friction sources and provide a quantitative evaluation. We particularly highlight the importance of frictions in conversions between fiat money and cryptocurrencies: arbitrage is harder in markets with higher trading volume, more crypto-exchanges in service, and domestic cryptocurrency supply (mining). Tighter capital controls also contribute to more Bitcoin arbitrage frictions. Finally, cryptocurrency regulations appear important; markets are more efficient in countries where crypto-trading is legally permitted and formally regulated under tax and anti-money laundering laws.

Our paper closely relates to three research areas. The first studies trust and finance. Trust broadly affects investment decisions and shapes financial contracts (e.g. Guiso et al. (2008), Guiso et al. (2004) , Guiso et al. (2006), Guiso et al. (2013), Sapienza and Zingales (2012), Gennaioli et al. (2020), and Caporale and Kang (2020)). Recent work argues that trust plays a critical role in financial intermediation and is crucial for stock market participation; see Gennaioli et al. (2015), Dorn and Weber (2017), Gurun et al. (2018) and Kostovetsky (2016). Our paper envisions the other side of the importance of trust in finance: *Distrust* induces the demand for cryptocurrencies.

Second, we contribute knowledge to the Bitcoin demand and limits of arbitrage in cryptocurrency trading.[2] Hautsch et al. (2018) and Makarov and Schoar (2019) document Bitcoin price deviations across currencies but leave the question of where the demand comes from.[3] Makarov and Schoar (2020) and Yu and Zhang (2018) document that

[2]A vast literature studies the limits of arbitrage in other financial markets. De Long et al. (1990), Shleifer and Vishny (1997), Gromb and Vayanos (2002), and Gromb and Vayanos (2018) investigate how arbitrage costs sustain mispricing. Rosenthal and Young (1990) and Froot and Dabora (1999) examine pairs of Siamese-twin stocks in different markets around the world with identical claims of cash flow but different prices. Mitchell et al. (2002) and Lamont and Thaler (2003) provide evidence on the price differences in the stocks of the parent company and its subsidiaries.

[3]Choi et al. (2018) study the price gap between Korea and the US and highlights capital controls in

policy uncertainties and Bitcoin price rallies expand the Bitcoin price deviations.

Our paper also contributes to the discussion of alternative monetary systems. Hayek (1978) argues that governments can defraud people and abuse their trust; thus, he advocates private bank money. Recent literature researches on blockchains and discusses their potential applications for de-nationalized currencies (Harvey (2016), Budish (2018), Biais et al. (2019), Ferreira et al. (2019), Cong and He (2019), Cong et al. (2019), Abadi and Brunnermeier (2018), Easley et al. (2019), Sockin and Xiong (2018), Catalini and Gans (2020), Auer (2019)), the cryptocurrency candidacies as new currencies (Yermack (2015) , Schilling and Uhlig (2019), Danielsson (2019)), and other redemption-based platform currencies (You and Rogoff (2020)).[4] Our findings show that distrust serves the needs for de-nationalized money.

Our paper is organized as follows. Section 3.2 documents the motivating facts: crypto-trading is more active in low-trust countries, and pervasive price deviations enable the opportunity to identify cross-country Bitcoin demand. Section 3.4 provides a theoretical framework of trust in portfolio choice and makes testable predictions. Section 3.5 brings empirical predictions to the Bitcoin trading data, investigates the determinants of price deviations, and highlights the importance of distrust on Bitcoin demand. Section 3.3 investigates the limits of arbitrage in crypto-trading. Section 3.6 explores the micro-foundations in trust, validates the model assumption, and discusses implications in investment strategies. Section 3.7 concludes.

2.2 Motivating Facts

2.2.1 Trust and Bitcoin Trading

We first show that Bitcoin trading is more active in countries with lower levels of trust.[5] The trust measure is from the Global Preference Survey (GPS), which asks respondents whether they assume that other people only have the best intentions.[6] In our

Korea.

[4]In additional to private money, Auer et al. (2020) and Auer and Böhme (2020) examine Central Bank Digital Currency (CBDC) as an alternative monetary system.

[5]The perfect data should be Bitcoin holdings by country; however, Bitcoin owners' nationality is not observable. We use fiat currencies traded with Bitcoin to capture the interest in Bitcoin across countries.

[6]GPS survey shows that this question was a strong predictor of trusting behavior in incentivized trust games, in the survey design stage.

sample, Japan (-0.51873) is the lowest trust country, and China (0.55281) is the highest trust country. Figure 2.1 Panel A shows the correlation between the trust level and log numbers of Bitcoins traded in the country's currency in 2019. Table 2.1 Column (1) reports that the slope is -3.83 (t=-2.18), which translates into 4.1 times if the trust level moves from the minimum to the maximum level.[7] We add more controls: population size, GDP per capita in Column (2), cryptocurrency regulations in Column (3), and capital controls and financial credit in Column (4).[8] The coefficient before *Trust* becomes larger with more robust statistical power. Columns (5)-(8) report the same set of regressions with Bitcoin traded per capita as the dependent variable. The negative relationship still holds.

Then, we examine how much cross-country variation in Bitcoin's popularity can be explained by the trust.[9] As total Bitcoin trading volume correlates with the population size and economic prosperity, we define the residual log trading volume $\widehat{Log\_Vol_c}$ as the unexplained error term orthogonal to population size (Pop_c) and GDP per capita (GDP_c). $\widehat{Log\_Vol_c}$ is estimated from the following regression:

$$Log\_Vol_c = \beta_1 Log(Pop_c) + \beta_2 Log(GDP_c) + \gamma + \widehat{Log\_Vol_c}$$

Figure 2.1 Panel B plots the correlation between the trust level and residual log volume. The negative slope increases to -4.56 (t=-3.62). Trust can explain 31.14% variation in the residual trading volume.[10]

2.2.2 Deviations from the Law of One Price

The role of trust is hard to identify, as trust is persistent and slow-moving. To address this issue, we turn to weekly price differences across currency as an indicator of Bitcoin demand and study how these price deviations respond to shocks differently in high-trust countries versus low-trust countries. Our core assumption is that a domestic Bitcoin demand boost can drive up the local Bitcoin price, relative to the dollar price, given the

[7] Japan yields the lowest trust score of -0.52, and China has the highest at 0.55.

[8] Section 2.5.4 provides detailed discussions on regulation variables.

[9] Foley et al. (2019) find that the share of Bitcoins used for illegal activities declines as mainstream investment interests turn to Bitcoin. Illegal activities tend to adopt cryptocurrencies even harder to trace.

[10] Table B.1 checks the robustness of the negative relationship, parallel to Table 2.1.

limits of arbitrage across country.

The Bitcoin prices quoted in different fiat currencies, converted into dollars with prevailing exchange rates, vary from country to country. On January 5^{th} 2020, the Bitcoin price was 8,024.58 USD. However, the Bitcoin was traded at 11,101.39 USD equivalent (578501.76 Peso) in Argentina. Argentine investors are willing to pay a 38% premium on that date. We define the price deviation as the price markup relative to the Bitcoin dollar price:

$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}}$$

$Prc_{c,t}$ is the price in the local currency of country c, and $Exchange_{c-USD,t}$ is the exchange rate from Bloomberg.[11] We obtain 5-year (Jan. 2015 - Jan. 2020) cryptocurrency prices and trading volumes from CryptoCompare.[12] The deviation should equal one if the law of one price holds perfectly.

Bitcoin price deviations can be astoundingly large. Figure B.1 plots the price deviations in Argentina and the United Kingdom from 2015 to 2020. During the 2018 Argentine monetary crisis, the maximum price gap in that country reached 37.14% in January. On the same date, the price difference was only 2.16% in the United Kingdom. Compared to the UK, Argentine Bitcoin prices are also much higher and volatile over time. Argentina is the country with the most expensive Bitcoins; it is 12.07% more expensive on average to buy Bitcoins there than in the US. Colombia is the country with the cheapest Bitcoins; they are 3.51% cheaper than US Bitcoins on average. Table 2.2 Panel A presents the summary statistics of price deviations across 31 countries in our sample. The average price deviation across all countries is 3.26%, and the standard deviation is 13.25%.

2.3 Theory

This section develops a simple model to introduce trust in the portfolio choice framework formally. We derive a closed-form solution for price deviations as a function of trust and other factors. With the model, we can deliver a set of testable empirical predictions

[11] Cryptocurrency trading in USD has the largest trading volume, and is also supported by most mainstream crypto-exchanges. We use the Bitcoin price in USD as the global benchmark price.

[12] CryptoCompare calculates daily cryptocurrency prices based on the 24-hour volume-weighted average among local exchanges. 24-hour volumes are calculated solely based on transactional data.

about Bitcoin price deviations to understand more about what elements affect the Bitcoin demand and how they interact with country-level distrust. In our model, distrust is defined as the perceived probability of being cheated. Investors suffer from financial loss when cheating happens.[13] Distrust is exogenous and time-invariant for a given country.

The model provides a theoretical framework to think about why trust matters in the demand for de-nationalized assets. The key model prediction is aligned with our main hypothesis in this paper that distrust in local institutions drives excess demand for cryptocurrencies across countries. All the empirical predictions in the next section are formalized and can be delivered from the simple model, which makes them easy to interpret.

Moreover, since there is no reliable data of cross-country Bitcoin demand in terms of volumes and holdings, the model illustrate how we can use price deviation to proxy cross-country Bitcoin demand given the same level of friction. Based on the supply and demand curve that determine the price deviation, the model provides a novel framework to understand how supply, demand, price deviation, distrust loss shock, and frictions interact with each other.

2.3.1 Model Setup

Assets

Three assets are available for investors. The local risky asset return R_L follows an exogenous log-normal distribution: $log(R_L) \sim N(\mu_L, \sigma_L^2)$. Investors perceive the cheating probability of p. If they are cheated, investors can only recover B percentage of return $R_l = BR_L$. The B is not observable and $b = log(B)$ has a mean of $\bar{b} < 0$ and a variance of σ_b^2.

A local risk-free asset with return RF_L (zero variance, $rf_L = log(RF_L)$) is also available for investors. Investors are not exposed to cheating if they put their money in the risk-free asset. For example, government bond yields are transparent in the market, and investors can quickly detect if any cheating happens. Thus, in equilibrium, no cheating happens to the risk-free asset.

[13] For example, investors can lose money from fraudulent behavior if a financial advisor takes bribes and misguides investors to put their money in low-quality projects, a listed company intentionally forges financial statements, or the government confiscates private properties.

Then, we introduce a global risky asset — cryptocurrency, e.g., Bitcoin — whose return R_G follows an log-normal distribution $log(R_G) \sim N(\mu_G, \sigma_G^2)$. Note that μ_G and σ_G are exogenous parameters, as we implicitly assume that Bitcoin demand in the local country does not change the global Bitcoin price. For simplicity, we assume that no global risk-free asset is available.[14] Cryptocurrencies do not expose to trust risks and provide the same returns for global investors. We make an important assumption here: The global risky asset functions as a substitute for the local risky asset, that is, cryptocurrency returns are positively correlated with the local stock returns: $Corr(R_G, R_L) = \rho > 0$. Under this assumption, investors would substitute local investments with Bitcoin when they trust less in their home countries. Empirically, we validate that $\rho > 0$ in Section 2.6.3.

Investors

We consider a representative cryptocurrency investor who is myopic with constant relative risk aversion (CRRA) γ. The investor optimizes the portfolio choice from all three assets by maximizing the expected utility: π_G of wealth invested in cryptocurrency, π_L of wealth in local risky investments, the rest allocated in the risk-free asset. For simplicity, we assume that the investor does not consider transitory price deviations for portfolio construction; thus, Bitcoin demand π_G is inelastic to the price deviation.[15]

$$\max_{\pi_L, \pi_G} E_t[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}]$$

[14]So far, there are no decentralized risk-free assets. The cryptocurrency closest to being risk-free is the stable coin Tether (or USDT), which is backed by USD reserves. However, Tether's audit system has been regarded as a significant risk for years. Tether's general counsel Stuart Hoegner admitted that only 74% of outstanding tokens are backed by cash or cash equivalents. Bitfinex — a major cryptocurrency exchange and Tether's sister company — borrowed money from its USD reserves and lacked transparency. Bitfinex exchange was accused by the New York Attorney General of using Tether's USD deposit to cover up a $850 million loss since mid-2018.

Tether is also much more rigid to acquire than Bitcoin. Many exchanges do not support direct USDT purchases because of Tether's controversial relationship with Bitfinex. Tether is not available to be legally traded due to conflicts of interests and its questionable use of reserves. For example, in India, investors can acquire Bitcoins from Zebpay, Coinexchange, Ethereum from Ethexindia, and Ripple from BTCxIndia, but not they cannot purchase USDT with Indian Rupees. To buy USDT, Indian investors must use an auxiliary currency, such as USD or BTC. BTC is usually paired with fiat currencies, and then investors use their BTC to buy other cryptocurrencies.

[15]The underlying assumption beyond is no inter-temporal substitution in Bitcoin demand; that is, a higher price deviation will not delay investors' demand for the next period.

Supply Curve

Then, we assume an ad-hoc linear cryptocurrency supply curve in the domestic market:

$$\frac{P_L}{P_{USD}} - 1 = \kappa(S - \bar{S})$$

where $\frac{P_L}{P_{USD}}$ is the transitory price deviation and $S - \bar{S}$ captures the excess Bitcoin supply.[16] The excess Bitcoin supply refers to the Bitcoin brought into the country by the international arbitragers to clear the local market, $S = \pi_G$. When the local demand surges, arbitragers need to provide more Bitcoin in the local country and require a larger price difference for compensation. Our model assumes that only arbitragers respond to price deviations and determine the supply curve, while investors' demand does not change with transitory price deviations.

κ is the price elasticity relative to the excess demand.[17] κ is the parameter that reflects the limits of arbitrage discussed in the Section 3.3. When market friction increases, a higher κ indicates a larger price change in response to the same demand shock. We assume no supply shocks in the economy; that is, the demand side drives price deviation changes only.

2.3.2 Asset Allocation and Trust

We first solve the model without the global risky asset and assess how distrust affects local risky asset investments.[18]

Proposition 1 (two-asset case): Portfolio weight π_L of the local risky asset

$$\pi_L = \frac{\mu_L - rf_L + \frac{1}{2}\sigma_L^2 + p(\bar{b} + \frac{1}{2}\sigma_b^2)}{\gamma(\sigma_L^2 + p\sigma_b^2)}$$

Comments: Distrust leads to under-investment, even non-participation in the domestic risky asset market. The numerator (approximately) shrinks by the average loss from cheating: $(\bar{b} + \frac{1}{2}\sigma_b^2) \approx log(E(B)) < 0$. B is universally smaller than one by the

[16] $\bar{S}$ is the Bitcoin supply in the long-run equilibrium. We assume the price deviation depends on the excess supply only.

[17] To be precise, $\frac{1}{\kappa}$ is the conventional definition of elasticity. In this paper, we always take price deviations as the dependent variable, and the Bitcoin demand quantity is not observable in the market. Thus, we define price elasticity as the price response to quantity shocks in our paper.

[18] See Appendix B.2.1 for math derivation.

definition of cheating. $log(E(B)) \approx E(B) - 1$ if B is not far below 1. Investors choose not to invest if domestic excess return $\mu_L - rf_L + \frac{1}{2}\sigma_L^2$ is lower than the expected loss from cheating $plog(E(B))$. Trust risk $p\sigma_b^2$ inflates the denominator, thus further lowering exposure to domestic risky assets.

How does the global risky asset change portfolio allocation? We denote excess return on the global asset as $\tilde{\mu_G} = \mu_G + \frac{1}{2}\sigma_G^2 - rf_L$, and net-of-cheating excess return on the local risky asset as $\tilde{\mu_L} = \mu_L - rf_L + p\bar{b} + \frac{1}{2}(\sigma_L^2 + p\sigma_b^2)$. Proposition 2 solves the portfolio weights in local and global risky assets.[19]

Proposition 2 (three-asset case): Portfolio weights in global and local risky assets:

$$\pi_G = \frac{1}{\gamma\sigma_G^2}\frac{(\sigma_L^2 + p\sigma_b^2)\tilde{\mu_G} - \rho\sigma_L\sigma_G\tilde{\mu_L}}{(1-\rho^2)\sigma_L^2 + p\sigma_b^2}$$

$$\pi_L = \frac{1}{\gamma\sigma_G^2}\frac{\sigma_G^2\tilde{\mu_L} - \rho\sigma_L\sigma_G\tilde{\mu_G}}{(1-\rho^2)\sigma_L^2 + p\sigma_b^2}$$

Distrust contributes to the cryptocurrency demand through its impact on $\tilde{\mu_L}$ and $p\sigma_b^2$. For a more straightforward interpretation, we expand the closed-form solution of π_G with the first-order approximation with respect to p.

Lemma: Linear approximation of the global risky asset demand (around $p = 0$):

$$\begin{aligned}
\pi_G = & \underbrace{\frac{1}{\gamma\sigma_G^2}\frac{\sigma_L^2\tilde{\mu_G} - \rho\sigma_L\sigma_G(\mu_L + \frac{1}{2}\sigma_L^2 - rf_L)}{(1-\rho^2)\sigma_L^2}}_{\Pi_G^b\text{:Demand without Distrust}} \\
& + \underbrace{\frac{1}{\gamma\sigma_G^2}\frac{\rho\sigma_G\sigma_L}{(1-\rho^2)\sigma_L^2}}_{\chi\text{:Lower Return Induced by Distrust}} [-(\bar{b} + \frac{1}{2}\sigma_b^2)]p \\
& + \underbrace{\frac{1}{\gamma\sigma_G^2}\frac{\rho(\frac{\sigma_G}{\sigma_L}(\mu_L + \frac{1}{2}\sigma_L^2 - rf_L) - \rho(\mu_G + \frac{1}{2}\sigma_G^2 - rf_L))}{(1-\rho^2)^2\sigma_L^2}}_{\eta\text{:Higher Risk Induced by Distrust}}\sigma_b^2 p
\end{aligned}$$

where $\chi > 0$ and $\eta > 0$.

Comments: The first term Π_G^b is the demand under perfect trust ($p = 0$). The second term is the demand proportionate to the average loss from cheating $(\bar{b} + \frac{1}{2}\sigma_b^2)p$ ($\approx E(B)$). The third term is proportionate to the trust risk σ_b^2, the uncertainty in cheating loss.

[19] See Appendix B.2.2 for math derivation.

Global risky asset demand increases in response to a) more audacious cheating $\chi > 0$, b) larger trust risk $\eta > 0$, and c) higher probability of cheating p. $\chi > 0$ is evident by the formula: the multiplier χ can be rewritten as $\frac{1}{\gamma}\frac{\rho}{1-\rho^2}\frac{1}{\sigma_L\sigma_G}$. Then, we can rewrite $\eta = \frac{\rho}{\sigma_L\sigma_G}\Pi_t^L$. Π_t^L, the demand for the local risky asset with perfect trust, must be positive as domestic investments are assets with positive net supply.

2.3.3 Empirical Predictions

Empirically, it is hard to distinguish between the average loss from cheating $E(B)$ and perceived trust risk σ_b^2. Thus, for simplicity, we assume $\sigma_b = 0$ and classify all information on institutional credibility into term $\bar{b}$. With the linear approximation, we can simply write the price deviation as follows:

$$\frac{P_L}{P_{USD}} - 1 = \kappa(-\chi bp + \Pi_G - \bar{S})$$

κ and b capture the time-varying market friction and perceived cheating loss, respectively. p is the country-level distrust, and also the probability of being cheated. χ is proportionate to risk appetite $\frac{1}{\gamma}$. Π_G is the trust-irrelevant Bitcoin demand, and $\bar{S}$ is time-invariant equilibrium Bitcoin supply.

We make empirical predictions on the determinant factors in price deviations and focus on the heterogeneous responses by country-level distrust. Figure 2.2 shows the shifts of supply and demand curves as a graphic illustration for the following predictions.

Prediction 1: Information on institutional failures expands price deviation.

$$\frac{d\frac{P_L}{P_{USD}}}{d(-b)} = \kappa\chi p > 0$$

Prediction 2: Price deviation response to institutional failures would be stronger in low-trust economies.

$$\frac{d\frac{P_L}{P_{USD}}}{d(-b)dp} = \kappa\chi > 0$$

Prediction 3: Price deviation extends when market friction κ increases. Distrust amplifies the effect.

$$\frac{d\frac{P_L}{P_{USD}}}{d\kappa dp} = -\chi b > 0$$

Prediction 4: Price deviation widens when risk appetite boosts. Distrust amplifies the effect.

$$\frac{d\frac{P_L}{P_{USD}}}{d\frac{1}{\gamma}dp} = -\kappa\frac{1}{\sigma_G\sigma_L}\frac{\rho}{1-\rho^2}b > 0$$

Prediction 5: Positive distrust loss *elasticity* (χ)

$$\frac{d\frac{P_L}{P_{USD}}}{d\kappa dpd(-b)} = \chi > 0$$

2.4 Empirical Tests

This section tests the five empirical predictions in crypto-trading data, particularly our unique prediction of heterogeneity by the trust level (p). We measure attention to institutional failures (b), country-specific frictions (κ), and changes in risk appetites (γ); we study their predictability in the domestic Bitcoin price deviation and document the significant role of trust.

2.4.1 Data Description

Our benchmark trust data is from the Global Preference Survey (GPS).[20] After merging the cryptocurrency dataset with GPS trust, there are 31 countries (USD and EUR excluded) in our sample.[21] Other trust-related variables — confidence in various local institutions and perceived corruption— are from the World Value Survey.

We use weekly Google Trend indices of the keywords "Conflict," "Crisis," "Scandal," and "Instability" to measure the institutional failures, and "Bitcoin," and "Gold" to capture attention to these assets. The maximum of an index scales to 100 given the sample period from January 2015 to January 2020.

[20] The trust data is based on a global preference survey of 80,000 individuals, drawn as representative samples from 76 countries worldwide. See Falk et al. (2018).

[21] The 31 countries in our sample are United Arab Emirates, Argentina, Australia, Brazil, Canada, Switzerland, Chile, China, Colombia, Czech Republic, United Kingdom, Croatia, Hungary, Indonesia, Israel, India, Japan, Kenya, South Korea, Mexico, Philippines, Pakistan, Poland, Romania, Russia, Saudi Arabia, Sweden, Thailand, Ukraine, Vietnam, and South Africa.

To study risk appetite, we assume that a high past return indicates that investors are more aggressive. We proxy risk appetite with Bitcoin returns and local stock market returns over past 8 weeks. The stock returns are from Compustat Global and North America.[22] For each country, we calculate value-weighted market returns for all companies whose headquarters ("LOC" in Compustat) are located in the country.

2.4.2 Event Studies on Price Deviation

Before testing model predictions, we start with event studies on price deviation. One may claim that price deviation captures both cryptocurrency demand and market friction, but it is less the case when the friction level is controlled. To do this, we manually identify the events behind Google search peaks of the four keywords: Conflict, Crisis, Instability, and Scandal. In total, 121 spikes are found for the four keywords to verify whether the Google search on "Conflict", "Crisis", "Scandal", and "Instability" reflect investors' concern for local institutional failures. 95 peaks can be found with concrete events, while we cannot identify events for the other 26 peaks. 78 spikes indicate domestic institution failures or crises, while the other 17 are driven by irrelavant events (e.g., sexual scandals). We classify the events into four categories: (1) Economical institutional failures, (2) Political institutional failures, (3) irrelevant events, and (4) Unknown events (i.e., events we can not identify). Appendix B.3 documents the full list of the events found with our endeavor.

Figure 2.3 plots the event study results on economical institutional failures and political institutional failures. For each event, we track the changes in price deviation in an event window of 16 weeks. Then we aggregate all the corresponding events in an equal-weighted manner. Panel A and B in Figure 2.3 show a consistent pattern that price deviation shifts up at the event date of institutional failures. To test the placebo, Figure 2.4 plots the event study results on irrelevant and unknown events, which are events that are not directly linked to local institutional failures. Both figures show that price deviation is volatile before and after the event date, and there is no dramatic shift in price deviation pattern at the event date. Table 2.3 reports the above four event studies on price deviation in a regression format. There is a 0.009 bps (t=1.78) and 0.014 bps

[22] Canadian stocks are from Compustat North America.

(t=4.67) increase in price deviation upon economical and political institutional failures, while the impacts from irrelevant and unknown events are insignificant.

The underlying assumption of our identification is that while perception in institutional failures change at the event date, market friction level is not expected to shift on the same date. To further validate the robustness, we investigate the heterogeneous response in countries with different level of capital control, which is documented as the most typical market friction in cryptocurrency markets.[23] To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open (least restrictive), Gate, and Wall (most restrictive). Figure 2.5 and 2.6 shows the event study results of the four types of events across countries of three capital control level. From the graph, we find no systematic difference across the groups. The patterns for "Open" economies and "Wall" economies are very similar. Table 2.4 reports the regression results of the event studies across countries of different capital control level on price deviation. There is no heterogeneity of the impacts in economic, political, and irrelevant events. For unknown events, price deviation response seems to be higher in countries with lower level of capital control. The robustness checks on capital control provide further evidence that the event is purely institutional failure shocks, with little relation to market friction changes.

2.4.3 Institutional Failures and Trust

We then move to our model predictions and start with Prediction 1. Google trend indices on "Conflict", "Crisis", "Instability", and "Scandal" to capture people's concerns about domestic institutional failures (b). To smooth out times series, we compute $GT_{c,t}$ as a discounted sum of Google search indices in the past eight weeks with a discount factor of 0.8.[24]

$$GT_{c,t} = \sum_{i=0}^{i=7} 0.8^i \times Google_{c,t-i}$$

where $GT_{c,t}$ is the cumulative Google Trend index in country c, and $Google_{c,t}$ denotes the raw Google Trend index.

[23]See Makarov and Schoar (2019) and Makarov and Schoar (2020)

[24]Our results are not sensitive to the choice of the discount factor. Results hold for another deflator from 0.6 to 1.

Table B.2 reports the correlation matrix among the $GT_{c,t}$ of four keywords. Google searches for “Conflict” have a 19.32% correlation with “Crisis”, a 48.58% correlation with “Instability”, and a 11.73% correlation with “Scandal”, respectively. “Crisis” has little correlation with “Instability” and “Scandal” (only -3.57% and 7.80% respectively). Similarly, “Instability” and “Scandal” are merely correlated as well (-10.21%).“Conflict” and “Instability” might capture similar events, but are quite orthogonal with “Crisis” and “Scandal.”

We regress price deviations on cumulative Google search indices one by one. To set a high bar for statistical significance, we cluster standard errors at the currency level (31 clusters) and adjust for heteroskedasticity in all regressions throughout the paper. Table 3.2 reports the results of the following regression:

$$Deviation_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t} \tag{2.1}$$

The price deviation expands by 2.68 bps ($t = 2.71$), 1.32 bps ($t = 2.07$), 2.13 bps ($t = 2.38$), 2.01 bps ($t = 2.81$) when the search indices of “Conflict,” “Crisis,” “Instability,” and “Scandal” rise by one unit, respectively. Scaled by standard deviations (s.d.) of indices, one s.d. move in cumulative Google searches correspond to a 1.74%, 0.78%, 1.44%, and 1.10% price deviation change, respectively. Investors buy more denationalized assets when they are more concerned about the risks of fragile institutions.[25]

Table 2.6 reports the impact of institutional failures on growth in attention to Bitcoin and trading volume. Column (1) shows that if a Google search for “Conflict” increases by one unit, the Bitcoin Google searches and Bitcoin trading volume increase by 10.0% (t = 4.52) and 11.1% (t=3.31), respectively. Columns (2) - (4) show similar results for the other three keywords.[26,27]

Before moving forward, we manually check the real events behind the Google search spikes. Table B.3 gives some examples of institutional disruptions that correspond to Google search spikes, including military conflicts, sovereign credit downgrades, monetary

[25]Table B.4 reports robustness check results when controlling Bitcoin returns and currency returns.

[26]In Table B.5, we add Bitcoin, stock, and currency returns to regressions. Institutional failures still predict a surge in “Bitcoin” Google search results at 1%. A Bitcoin price rally is the most potent trigger for interests in Bitcoin, with t-stat above 30.

[27]Table B.6 reports the results for Google searches on “Gold”. Institutional failures overall correspond to higher search volumes on “Gold”; however, it is not statistically significant.

system crisis, political and corruption scandals. Appendix B.3 reports the event searching for all 121 Google search spikes. We can identify 95 events, while other the other 26 peaks cannot be matched with any news. 78 events, out of 95, are directly related to local institutions or politics. Almost no domestic search spike links to international news or events in other countries.[28]

Then, to test Prediction 2, we examine the role of trust in explaining the price response heterogeneity across countries. Based on the trust score from the Global Preference Survey, we divide the countries in our sample into three groups: 11 high-trust countries ($Trust \in [0.2, 1)$), 9 medium-trust countries ($Trust \in [-0.1, 0.2)$), and 11 low-trust countries ($Trust \in [-1, -0.1)$). In addition, we define the variable $Distrust$ as

$$Distrust = 1 - Trust$$

Table 2.7 Columns (2) - (4) report the regression results in Eq.(2.1) by country category. For the keyword "Crisis" one unit increase in the Google search results predicts the price deviation increases by 4.52 bps (t = 2.70) and 4.59 bps (t = 2.00) in medium-trust and low-trust countries, but almost no impact (-0.31 bps t = -0.47) in high-trust countries. In Column (5), we include the interaction term for cumulative Google search and $Distrust$, and run the following regression:

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

The coefficient β_2, which captures how the price response varies across the spectrum of trust, is 8.53 (t = 2.95). It is consistent with the results in Columns (2) - (4) that societies with lower trust levels are prone to chase cryptocurrencies more when concerns about institutions exacerbate. Table B.7 presents the results for the other three keywords ("Crisis," "Instability," and "Scandal") and shows a similar pattern.[29]

However, trust can correlate with many other country features (e.g., Zak and Knack (2001)). We horse-race distrust with other vital aspects of a country, including GDP per capita, credit by financial sector, the rule of law, government effectiveness, and corruption

[28]Irrelevant events can be sexual scandals, corrupt sports teams, discussion on historical armed conflicts, etc.

[29]The effects are mainly concentrated and more pronounced in low-trust countries, with the loadings on Google trend 2.51 (t = 2.77), 2.72 (t = 2.18), 1.48 (t = 4.30).

scores.[30] Table B.8 reports the horse-racing regressions:

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \beta_3 Covariate \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

Column (1) reports the result of the original specification (as in Table 2.7 Column (5)), and Columns (2) - (6) show the horse-racing results with the five co-variates. The rule of law takes the coefficient down the most, from 8.53 ($t = 2.95$) to 4.52 ($t = 4.10$). The statistical significance slightly increases, although the coefficient magnitude typically slips after controlling country features. The horsing-racing regressions confirms that distrust delivers unique explanatory power and cannot be easily substituted.

2.4.4 Crypto-market Frictions

Then, we move to Prediction 3 on crypto-market frictions and trust. We propose return asynchronization to measure the magnitude of frictions under the assumption that arbitrage is more challenging if the domestic Bitcoin returns are less correlated with the Bitcoin dollar returns. The return asynchronization is formally defined as 100 minus correlation (in %) between the Bitcoin returns in local currency and the Bitcoin USD returns in a rolling window of 8 weeks.

$$Asyn_c = 100 - Corr(Ret_c^{BTC}, Ret_{USD}^{BTC})$$

where Ret_c^{BTC} is the Bitcoin return in local currency and Ret_{USD}^{BTC} is the USD return. A higher return asynchronization implies more disconnection with the international Bitcoin trading market, in other words, more frictions to arbitrage.[31] If there is no cross-border friction, the return of the same asset should co-move perfectly in different countries. To justify that return asynchronization is an ideal proxy for market friction, we investigate

[30] GDP and financial credit (% GDP) are from the World Development Index; the rule of law, government effectiveness, and corruption scores are from Worldwide Governance Indicators.

[31] We first evaluate the relationship between return asynchronization and price deviation at the country level on the first and second moments. First, Bitcoins are more expensive in markets with higher friction. Figure B.2 plots the relationship between the average return asynchronization and average price deviation by currency. One percentage point increase in asynchronization corresponds to 12 bps (t = 3.01, R-squared = 0.23) price deviation on average. A higher price premium provides more incentives for arbitragers to bring more Bitcoins into the country. More arbitrage frictions also correspond to a more volatile price deviation. Figure B.3 checks a relationship between the average return asynchronization and the standard deviation of price deviation by currency. These two measures yield a 56% correlation (t = 6.25).

its validity in terms of specific limits of arbitrage in this market including capital controls, market liquidity, market structure, law and regulations, and Bitcoin mining. Section 2.5 verifies that the correlation measure captures these frictions in a sensible manner, thus serving as a good proxy for market asynchronization.[32]

Table 2.2 Panel A reports the summary statistics of return asynchronization across 31 countries. The average return asynchronization across all countries is 24.67%, and the standard deviation is 29.33%. Among the 31 countries, Saudi Arabia has the highest average return asynchronization at 44.99%, while Japan has the lowest average at 1.73%.

Table 2.8 reports regressions of price deviations on the return asynchronization. Column (1) reports the results for all countries. In the full sample, deviation is boosted by 8.55 (t = 4.35) bps if return asynchronization increases by one percent. Columns (2) - (4) show the heterogeneity among countries with different trust levels. In high-trust countries, medium-trust countries, and low-trust countries, one percent increase in return asynchronization corresponds to 4.27 bps (t = 3.73), 7.63 bps (t = 1.94), 13.92 bps (t = 3.35) appreciation in price deviation. The coefficients increase monotonically: low-trust countries respond three times more aggressively than high-trust countries.

Table 2.8 also reports the mean and standard deviation of return asynchronization for each country group. The standard deviations from high to low-trust group are 33.41%, 32.98%, and 31.88%, and imply 1.43%, 2.52% and 4.44% price response to a one standard-deviation change in return asynchronization.

$$Deviation_{c,t} = \beta Asyn_{c,t} + \gamma_c + \epsilon_{c,t}$$

We add the interaction term with distrust in Column (5). The coefficient β_2 is 0.11 (t = 2.20), consistent with Prediction 3.

$$Deviation_{c,t} = \beta_1 Asyn_{c,t} + \beta_2 Asyn_{c,t} \times Distrust_c + \gamma_c + \epsilon_{c,t}$$

[32] In particular, the following five facts substantiate the validity of the measure: (1) Return asynchronization is higher in countries with more restrictive capital controls. (2) One unit increase in market liquidity predicts 2.83 (t=-6.26) decrease in return asynchronization (R-squared: 56.6%). (3) The average return asynchronization decreases in the number of exchanges allowing trading in the currency. (4) Frictions are smaller in well-regulated countries and those without crypto bans. (5) Return asynchronization is 14.4% lower in production countries.

2.4.5 Risk Appetite

Prediction 4 indicates that risk-chasing enlarges the Bitcoin price deviation, and the expansion is larger in low-trust countries, particularly. We use the past eight-week cryptocurrency returns and local stock market returns to proxy the risk appetite change of global crypto-investors and domestic investors. Our implicit assumption is that asset price rallies, at least partially, derive from excess buy-in, and vice versa.

Table 2.9 reports the results of the regression of local price deviations on the past Bitcoin returns.

$$Deviation_{c,t} = \beta Ret^{BTC}_{USD,t-9\to t-1} + \lambda Ret^{BTC}_{USD,t-9\to t-1} \times Distrust_c + \gamma_c + \epsilon_{c,t}$$

Column (1) shows that one percent increase in past eight-week return leads to 1.19 bps ($t = 2.75$) increase in the price deviation on average. Columns (2) - (4) show the estimate by trust level: 0.43 bps ($t = 0.55$) in high-trust countries, 1.56 ($t = 1.75$) in medium-trust countries, and 1.66 ($t = 2.76$) bps in low-trust countries. The effects of risk appetite on local price deviations are mainly concentrated in medium and low-trust countries as well. The coefficient of interaction term in Column (5) is 3.11 ($t = 2.15$).[33]

We further study the impact of stock market returns (value-weighted) to explore the cross-country variation in risk appetite changes. $Ret^{Stock}_{c,t-9\to t-1}$ refers to the log cumulative returns over the past eight weeks. Table 3.8 Columns (1) - (4) report the results:

$$Deviation_{c,t} = \beta Ret^{Stock}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

and Column (5) report the regression with interaction term:

$$Deviation_{c,t} = \beta_1 Ret^{Stock}_{c,t-9\to t-1} + \beta_2 Ret^{Stock}_{c,t-9\to t-1} \times Distrust_c + \gamma_c + \epsilon_{c,t}$$

In low-trust countries, price deviation is boosted by 8.0 ($t = 3.83$) bps if the past stock return goes up by one percent. In contrast, the coefficient shrinks to 1.89 ($t = 1.83$) in medium-trust countries and loses economic meaning and statistical significance in high-trust countries. The coefficient of interaction term in Column (5) is 10.49 ($t = 1.77$). A

[33]Table B.9 applies the same specification to Ethereum, and suggests our findings apply to other cryptocurrencies as well.

domestic stock rally simultaneously drives the demand for Bitcoin, mainly in low-trust countries as well.

However, it is likely that past returns in local and global markets contain other information that does not reflect risk appetite. Thus, it is necessary to check other proxies that may capture different dimensions of risk appetite. To check the robustness, we investigate alternative measures of risk appetite including realized volatility and skewness. Realized volatility measures the amount of uncertainty about the fundamental factors that drive asset prices, which influences investors risk appetite. It is also that the skewness of return distribution is affected by investors risk attitudes; their risk seeking increases the return skewness while risk aversion decreases the return skewness. We calculate realized volatility and skewness using past eight-week Bitcoin return data in each country. Then we investigate the price responses to realized volatility and skewness, as well as the heterogenous effects by country's trust level. Table B.20 reports the price deviation response to realized volatility, which shows a consistent pattern that realized volatility can positively predict price deviation and the effects are more pronounced in low-trust countries. Table B.21 reports the price deviation response to skewness, which does not seem to be a factor driving price deviation.

2.4.6 Distrust Loss Elasticity

We estimate the distrust loss elasticity χ as in Prediction 5: the cryptocurrency demand response to a unit change in the cheating loss Bp. We identify χ with the quasi-triple difference-in-differences specification:

$$\begin{aligned} Deviation_{c,t} =& \beta_1 Asyn_{c,t} + \beta_2 \lambda Asyn_{c,t} \times Distrust_c + \beta_3 GT_{c,t} + \beta_4 GT_{c,t} \times Asyn_{c,t} \\ &+ \chi GT_{c,t} \times Asyn_{c,t} \times Distrust_c + \gamma_c + \epsilon_{c,t} \end{aligned}$$

To make elasticity χ interpretable, we normalize price deviation, Google trend, and return asynchronization to a standard normal distribution for each country, and linearly re-scale distrust to [0,1].[34] χ represents the cryptocurrency demand response to one s.d.

[34] Japan is set to one with the highest distrust level (-0.52 in GPS). China is assigned to zero with the highest trust level (0.55 in GPS). Other countries linearly interpolate accordingly.

move in perceived loss from distrust under a conceptual environment with the highest distrust and perfect isolation from the US crypto-market (return asyn. = 100%).

Table 2.11 reports the elasticity estimation with the four Google search keywords. "Conflict" yields the highest estimate — One s.d. cheating loss corresponds to 0.62 (t = 2.20) s.d. demand increase in Bitcoins. "Instability" gives a similar estimate of 0.58 (t = 1.99), while the "Crisis" and "Scandal" estimates are relatively smaller at 0.47 (t = 1.40) and 0.33 (t=0.78), respectively. The statistical power is limited as we include four interaction terms in the specification; and we set a high bar for statistical significance—standard errors are clustered by currency and heteroskedasticity is adjusted. χ estimates, ranging from 0.33 to 0.62, are positive, thus broadly consistent with Prediction 5.

2.5 Limits of Arbitrage

We use return asychronization—the quantitative measure of frictions' magnitude—as the slope of the Bitcoin supply curve; however, no prior research investigates why return asychronization is exceptionally high in some countries (e.g., Saudi Arabia) but very low in other countries (e.g., Japan), nor does any literature explore the validity of the correlation measure in capturing cross-border market asynchronization and frictions. To justify that return asynchronization is an ideal proxy, we investigate the specific frictions in terms of the limits of arbitrage existing in this market including capital controls, market liquidity, market structure, law and regulations, and Bitcoin mining.

To start with, we analyze the typical frictions that prevents arbitrage trades across countries from an arbitrager's perspective. An arbitrager needs to proceed with the following these steps to take advantage of the price difference:

1. Convert US dollar into Bitcoin;

2. Send Bitcoin from exchange wallet to private wallet;

3. Send Bitcoin from private wallet to an exchange where the arbitrager can sell Bitcoin for local currency directly;

4. Sell Bitcoin for local currency under the exchange's bank account;

5. Transfer funds to the bank account in local country;

6. Convert local currency back to USD and take the money out of the local country.

Many barriers can arise in this procedure and prevent arbitragers from acting; thus, leading to a positive-sloping Bitcoin supply curve in the short run. Capital controls (Step 6) have been widely studied and argued as are the primary reason for the price deviations across countries in the literature.[35] In additional to capital control that prevents trading between fiat currencies, we also investigate other frictions in trading between cryptocurrency and fiat money that play a critical role in the short horizon.

Through examining different types of frictions in the Bitcoin arbitrage and evaluating how these frictions explain the cross-country variation in return asychronization, we document five facts substantiating the validity of the return asynchronization measure: (1) Return asynchronization is higher in countries with more restrictive capital controls. (2) One unit increase in market liquidity predicts 2.83 (t=-6.26) decrease in return asynchronization (R-squared: 56.6%). (3) The average return asynchronization decreases in the number of exchanges allowing trading in the currency. (4) Frictions are smaller in well-regulated countries and those without crypto bans. (5) Return asynchronization is 14.4% lower in production countries.

In the following sections, we first investigate capital controls — the conventional explanation — then examine crypto-fiat liquidity, market segmentation, Bitcoin mining, and legal perspectives.

2.5.1 Capital Controls

Since September 2019, Argentine companies have been subject to a central bank rule that requires them to repatriate all export earnings back and convert those earnings into pesos at the official exchange rate set by the central bank. Further, companies have been subject to central bank approval to access US dollars. Simultaneously, as shown in Figure B.1, Argentine Bitcoin price surged to 40% more expensive than the dollar price while the central bank tightened the capital controls in Argentina.

Under tight capital controls, institutional arbitragers would face more challenges when sending money out of the country and might not convert local currencies to USD at a desirable exchange rate. To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open

[35]See e.g. Makarov and Schoar (2019) Makarov and Schoar (2020), Yu and Zhang (2018), Choi et al. (2018)

(least restrictive), Gate, and Wall (most restrictive). Small retail arbitragers face the cross-border money transfer costs if they want to take advantage of price differences. We proxy retail transfer costs with the exchange rate margin charged by the vendor recommended by *Monito.com* and the average margin and transaction fee recorded by the World Bank Remittance Survey.[36]

Table B.10 correlates the average return asynchronization with the capital controls and retail transaction costs. Return asynchronization is higher in countries with more restrictive capital controls: 7.1% for five "Open" countries, 19.1% for twenty "Gate" countries, and 24.3% for five "Wall" countries. However, as reported in Columns (1) and (2), no more than 13.34% of variation can be explained by the capital control measure. Moreover, we do not find that retail transfer costs correlate with the return asynchronization, as shown in Columns (3) - (6). Our findings confirm that return asynchronization measure captures the variation of frictions in capital control.

2.5.2 Insufficient Liquidity

Beyond capital control, we also see price deviations even in countries with no exchange rate controls. For example, Sweden imposes little capital control and is labeled as "Open" in Fernández et al. (2016). However, the Swedish Bitcoin price is 5.82% higher than the dollar price, and its returns are only 75% correlated with the dollar returns. The first conjecture is the shortage of liquidity. The total trading volume in Sweden is only 1,214 BTC in 2019, while the trading volume in USD is 16,702,356 BTC.[37] Arbitragers either fail to find enough Bitcoin buyers in Sweden or cannot sell a large number of Bitcoins without bringing the Sweden Krona price down.

We explore whether the trading volume can explain the cross-country variation in return asynchronization. Figure B.4 plots the average return asynchronization and log Bitcoin trading volume in 2019. One unit increase in log(volume) predicts 2.83 (t=-6.26) decrease in return asynchronization. The R-squared is 56.6%. Our findings confirm that return asynchronization measure captures the variation of frictions in market liquidity.

[36] Rates are not available for most money corridors from local countries to the United States. Thus, we use the transfer costs of corridors from the United States to other countries.

[37] The real trading volume can be even lower than the data shows. Cong et al. (2020) imply that crypto-exchanges frequently use wash trading to fake volume.

2.5.3 Segmented Trading Markets

Then, we dive into the market structure of cryptocurrency trading. In Sweden, investors typically trade cryptocurrencies through peer-to-peer OTC platforms, such as LocalBitcoins and Bisq.[38] Arbitragers can only sell a tiny number of Bitcoin at a time; for example, the order size per advertisement was limited to 150 - 1,200 SEK on October 8^{th}, 2020; on that date, the Bitcoin price was 98,844.25 SEK. Arbitragers need to post many advertisements and risk that retail buyers might not accept these offers.

Cross-currency arbitrage can be costly even in countries with exchanges to facilitate trading. Korea has six active cryptocurrency exchanges: Huobi Korea, GOPAX, Korbit, Coinone, UPbit, and Bithumb Korea. However, all these exchanges only have active trading in Korean Won—almost no investors buy or sell with US dollars. Arbitragers need to send Bitcoins from a US exchange to a Korean exchange and typically pay various transaction fees: Binance charges 0.04% to withdraw Bitcoin, Coinbase charges 1.49% for fiat currency transactions in the US.[39,40] Sending Bitcoin across exchanges typically would take 30-60 minutes to complete, depending on the blockchain network's congestion. Arbitragers have to bear the risk of price changes during this period.

To quantify cryptocurrency market segmentation, we manually collected trading volume in the last 24 hours from the top 100 crypto-exchanges (ranked by CryptoCompare) on June 10^{th} 2020, and only 75 were active. We compute volume share as the number of Bitcoin traded in one currency divided by total Bitcoin traded on the same exchange. Then, we define the primary trading pair as the currency with the highest volume share. Figure B.5 counts the number of exchanges by the volume share of the primary trading pair. 37 out of the 75 exchanges, de facto, only execute trading in one unique currency. Multi-currency trading is only active listing platforms or OTC markets without automated market-making; for example, Localbitcoins and Bisq are the two exchanges in the bracket "20-40%" trading volume from the primary trading pair.

Trading volume depletes if we look beyond the primary currency used in the exchange. Figure B.6 summarizes the average volume share of the top 5 active trading pairs. The primary currency accounts for 87.9% of total volume. The number rapidly drops to 8.8%

[38]See Appendix B.5.3 for the details about OTC platforms.
[39]https://www.binance.com/en/fee/depositFee
[40]https://help.coinbase.com/en/coinbase/trading-and-funding/pricing-and-fees/fees

for the second functional currency, 2.2% for the third, 0.8% for the fourth, and 0.3% for the fifth. It is difficult to implement arbitrage across currencies within one exchange.

For each country, we further count how many exchanges officially accept its fiat currency for cryptocurrency purchase (although the actual volume can be zero). Figure B.7 plots the average return asynchronization by the number of exchanges allowing trading in the currency. The average return asynchronization is 38.76% for the 8 currencies with no coverage in the top 100 exchanges. The number decreases to 26.39% for the 7 countries with only one exchange, 21.10% for the 6 countries with 2 to 3 exchanges, 17.80% for the 5 countries with 4 to 5 exchanges, and 10.85% for the 6 countries with more than 5 exchanges. Our findings confirm that return asynchronization measure captures the variation of frictions in market structure.

2.5.4 Laws and Regulations

In September 2017, China announced its plan to crack down on cryptocurrency exchanges. Bitcoin trading volume in China plummeted by over 99%. Figure B.8 shows the rise of return asynchronization after the ban became effective in November.[41] Since September 2017, the return asynchronization rose from around 5% to 80% until April 2018. We use the return asynchronization in Hong Kong as a placebo, and it does not respond to the Chinese ban.

Regulations can occur at any stage of the arbitrage. Holding and trading cryptocurrency might be unlawful; regulators can crack down on exchanges; withdrawals of fiat money crypto-exchanges might be subject to capital taxation or anti-money laundering scrutiny. Different countries have different attitudes towards, and legal statuses for cryptocurrency. We manually code cryptocurrency regulations from *Regulation of Cryptocurrency Around the World report* compiled by The Law Library of Congress. Appendix B.4 details the laws and regulations of the 31 countries in our sample (USD and EUR excluded). The most crucial dichotomy is whether cryptocurrency trading is legal or not. The United Arab Emirates, Pakistan, and Vietnam explicitly define cryptocurrency as unlawful. Colombia, China, Indonesia, Pakistan, Saudi Arabia, and Thailand implicitly

[41]See Auer and Claessens (2018) for a comprehensive event study of 151 regulatory events on crypto-assets.

ban or announce policies against cryptocurrencies.[42]

We further look into countries where crypto-trading is legal and investigate their efforts to combat tax evasion and anti-money laundering. Australia, Canada, Switzerland, Czech Republic, Japan, and Korea enact anti-money laundering law specific to cryptocurrencies; Argentina, Brazil, United Kingdom, Israel, Kenya, Mexico, Sweden, and South Africa issue anti-money laundering warnings. Argentina, Australia, Canada, Switzerland, United Kingdom, Israel, Japan, Poland, Romania, Russia, Sweden, and South Africa propose tax laws for cryptocurrency trading.[43]

Table B.11 reports the relationship between return asynchronization and regulations. Among 31 countries, 6 countries do not impose any cryptocurrency regulations. Column (1) implies the 6 unregulated countries experience 13.50% (t = -3.34) higher return asynchronization on average. Within the 25 countries with regulations, Column (2) shows cryptocurrency bans (implicit and explicit pooled) raise return asynchronization by 5.71% (t = 2.12) on average. Unregulated markets and crypto-bans make it difficult to find reliable exchanges to convert fiat currency into and out of cryptocurrencies. Columns (3) and (4) evaluate tax and anti-money laundering laws. Return asynchronization decreases by 7.20% (t = -1.88) and 2.98% (t = -0.72), respectively. Figure B.9 plots return asynchronization by regulatory regimes. Most countries below 10%—Russia, South Africa, Israel, Canada, Japan, Poland, and Pakistan—recognize Bitcoins as a legal investment and collect tax on them.[44] Our findings confirm that return asynchronization measure captures the variation of frictions in law and regulation.

[42]A standard implicit ban targets crypto-exchanges or forbids domestic banks to open a corporate bank account for the exchanges. In this way, cryptocurrency exchanges cannot receive money from investors; thus, investors cannot easily trade with others. There are many ways to circumvent the legal ban, for example: work with foreign banks or construct an OTC market. Note that local authorities cannot touch the OTC platforms in most cases since OTC platforms do not need a fiat currency bank account in the local economy. Investors on OTC platforms send fiat currency to their trading counter-party's bank account directly, rather than through the OTC platform's bank account. We still see substantial trading activities, even after countries take legal actions against Bitcoin.

[43]For each country, we also record the date of the cryptocurrency ban, tax law application, and application of anti-money laundering laws. The vast majority of regulations started to crowd in after the Bitcoin price reached 1000 dollars in 2017.

[44]India is the only exception where Bitcoin is officially banned. However, domestic investors can still purchase Bitcoins with Rupee from many vendors. See https://www.buybitcoinworldwide.com/india/.

2.5.5 Concentrated Bitcoin Mining

China is a country where cryptocurrency is legally banned, and strict capital controls have been in place for decades. However, Bitcoin is only 1.31% more expensive than the dollar price, and its average return asychronization is below 10%. Why is that? One possibility is that Bitcoin miners play the role of arbitragers who can sell Bitcoin when the price deviation is too high, and essentially synchronize the Chinese price with the dollar price. China controls roughly 81% of the hashrate of global mining pools.[45] This section documents Bitcoin is cheaper, and its returns are more correlated with dollar returns in countries with Bitcoin production.

We define the production countries as those contributing more than 1% hashrate in Bitcoin mining. Besides China, the Czech Republic accounts for 10%, Iceland, Georgia, and Japan contribute by 2%; and Russia adds mining power by 1%. Four countries with more than 1% hashrate appear in our sample: China, the Czech Republic, Japan, and Russia. The average return asynchronization is 14.4% (t = -2.01) lower in production countries than non-production countries. The average price deviation is 2.7% (t = -1.34) lower in production countries than in other countries.[46] Our findings confirm that return asynchronization measure captures the variation of frictions in concentrated Bitcoin mining.

2.6 Discussion

This section discusses miscellaneous issues. We first document algorithmic trust brought by cryptocurrency and investigate sources of country-level human trust. Then, we validate our model assumption—the positive correlation between local stock market returns and cryptocurrency returns. Last but not least, we conduct robustness checks to rule out the role of exchange rate in driving the results, and control multiple factors to check the impact from institutional failures and distrust.

[45] https://www.buybitcoinworldwide.com/mining/pools/

[46] According to the Cambridge Center for Alternative Finance (https://cbeci.org/mining_map), the actual ownership of mining power in China is 65.08%, and the US is second with 7.24%. Russia, Kazakhstan, Malaysia, and Iran ranked from third to sixth with 6.90%, 6.17%, 4.33%, and 3.82% respectively, while other countries are all below 1% in the Bitcoin supply. Only China and Russia are in our sample with active crypto-trading and their average return asynchronization and average price deviation are lower by -15.5% (t = -1.55) and -3.29% (t = -1.19), respectively.

2.6.1 Algorithmic Trust

The foremost question is why investors turn to Bitcoin when they experience less trust? One of the most important feature of cryptocurrencies is the adoption of blockchain technology which replaces human trust in centralized authorities with algorithmic trust. Blockchain—a distributed, decentralized, public ledger—is a "trust machine" that uses an algorithm to verify and process transactions. No trusted authority is needed for people to collaborate, as the algorithm is governed by democracy and will not exploit any agent on the blockchain.[47] Blockchain makes sure that issuers cannot manipulate tokens once the rule enters the system. For example, the total quantity of Bitcoin is set to 21 million. There will not be any further token offerings or buybacks. Issuers cannot benefit from any asymmetric information nor can they potentially exploit investors.

Investors can directly control their cryptocurrency without any third-party or contracting; this security level is the same as gold bullion storage.[48] The private key, a variable in cryptography used to encrypt and decrypt code, fully defines cryptocurrency ownership. Investors' property rights are secured as long as holders can safely keep their private keys. Private keys can be held in digital wallets, Excel files, and can even be written on paper.[49] Moreover, blockchains can provide better security for transactions. Innovators endeavor to create decentralized marketplaces so that Bitcoin holders can trade without delegating their Bitcoins or fiat money to any exchange.[50] At that stage, users can store, spend, and trade crypto-assets without any intervention by third parties.

2.6.2 Economic Foundations of Distrust

The reason that we use trust metrics instead of other metrics for government credibility is due to the central hypothesis of this paper, that is, distrust in local institutions drives demand for cryptocurrencies across countries. As cryptocurrency is a new asset class that replaces human trust with digital trust, we believe that trust is the essential fac-

[47] Appendix B.5.1 discusses how PoW and PoS protocols validate transactions.

[48] The public-private key cryptography ensures that cryptocurrency transactions and storage are safe. Public keys are publicly known and essential for identification, while private keys are kept secret and used for authentication and encryption. The private key grants a cryptocurrency user ownership of the funds at a given address.

[49] Appendix B.5.2 thoroughly discusses the approaches for crypto-storage to balance security and convenience.

[50] Appendix B.5.3 discusses common approaches for crypto-trading.

tor rather than government characteristics. For example, it is likely that a country has a poor government, but people still trust the government so that there is no excess demand for cryptocurrencies. Therefore, we focus on trust measure that captures institutional fragility and government credibility that is perceived by people across countries.

Distrust measure in Global Preference Survey (GPS) is a general distrust measure that captures the general trust level in different countries. We use GPS measure in our main analysis for two reasons. First, GPS measure covers the most number of countries in our sample compared to other measures. Second, GPS measure potentially captures distrust in institutions in multiple aspects, while each other trust measures only capture one specific aspect, e.g., banks, government, companies, and corruptions.

To check the validity of GPS measure as a general trust measure capturing different aspects of distrust in institutions, we analyze the World Value Survey (WVS) to understand why people from some countries trust more than those from other countries. WVS enables us to construct cross-country measures of confidence in institutions and perceived corruption in various organizations.[51] For each specific question about a respondent's confidence level in banks, major companies, government, politics, and civil service, WVS reports the percentage of respondents in each of the four categories of confidence level. We assign weight 2 to "A great deal of confidence," 1 to "Quite a lot confidence," -1 to "Not very much confidence," -2 to "None at all," and 0 to "Don't know" or "No answer." We calculate the confidence score as the weighted average of the respondents in each category. Similarly, for each question about perceived corruption in business, civil service, local and state government, we assign weight 2 to "None of them", 1 to "Few of them", -1 to "Most of them", -2 to "All of them", and 0 to "Don't know" or "No answer". The corruption control score is the weighted average of the respondents in each category. The scale of the score is $[-200, 200]$.

Trust is positively correlated with confidence in institutions. Figure B.10 and Table B.12 show one unit more trust predicts 112.7 points ($t = 2.40$) more confidence in banks, 50.83 ($t = 2.10$) for companies, 128.1 ($t = 3.05$) for government, 108.1 ($t = 2.59$) for politics ,117.0 ($t = 3.69$) of civil service, and 119.3 ($t = 3.11$) for justice.

People who distrust more also believe that corruption is more common. Figure B.11

[51]WVS has seven waves of its survey. The countries covered in each wave are slightly different. In our analysis, we use the data from the latest wave (Wave 7). For the countries that are not covered by Wave 7, we employ the data from Wave 6. and so on. 17 countries in our sample can be matched in WVS.

and Table B.13 report the relationship between trust and the perceived control of corruption in business, civil service, local and state government. Trust corresponds to less perceived corruption, with a slope of 65.17 (t = 2.15), 85.10 (t = 2.18), 100.9 (t = 2.25), 69.73 (t =1.92), respectively.

As Falk et al. (2018) confirms trust measure in GPS is consistent with the WVS, we also validate the correlation between GPS trust and WVS trust in our country sample. WVS has questions regarding general trust in most people, trust people you know personally, trust people you first meet, and trust your neighbor. As before, we assign weight "2" to "Trust completely", "1" to "Trust somewhat", "-1" to "Do not trust very much", "-2" to "Do not trust at all", and "0" to "Don't know" or "No answer". We define the country-level WVS trust score as the weighted average of the respondents in each category. Table B.14 shows that one unit increase in the trust measure in GPS corresponds to 20.92 (t = 2.01), 67.13 (t = 1.96), 60.38 (t = 2.31), 46.24 (t= 1.51), respectively. The R-Squared of the above regressions are 13.43%, 15.47%, 20.31%, 9.78%, respectively. These results further validate that the two sets of trust measures are consistent.

2.6.3 Assumption Validation

The foundational assumption is that cryptocurrencies are substitutes for domestic investments. With the CRRA utility, $\rho > 0$ implies the substitution across asset classes—investors would allocate more to cryptocurrency when domestic investments become less appealing or riskier.[52]

We validate stocks and cryptocurrencies co-movement, which is $\rho > 0$.[53] In Table B.15, we regress the log BTC/ETH returns on the log value-weighted stock returns in Columns (1) and (2). A 1% increase in log stock return predicts a 0.24% BTC return and 0.49% ETH return. The raw correlations are 5.45% and 5.56%. We further aggregate stock market returns into a weekly time series with all 31 countries equally weighted. Columns (3) and (4) report the time-series regressions: A 1% change stock return translates into 1.39% Bitcoin return, and 2.92% ETH return. The time-series correlation soars to 13.18% for BTC and 13.39% for ETH.

[52]If Bitcoin is a hedging asset, an investor would demand less as they reduce the exposure to domestic assets.

[53]Many market factors drive both the stock prices and cryptocurrency prices in the same direction. Risk-seeking, interest rate reduction, and quantitative easing can move both prices higher.

Furthermore, we check the robustness with the monthly returns of stock indices from Compustat Global. In total, 24 out of 31 countries remain in our sample with valid data of stock indices. We compute the correlation between stock and Bitcoin/Ethereum for each country. Figure B.12 plots the kernel densities of these two return correlations. The average monthly correlation is 18% between the stock index and Bitcoin, and 23% for Ethereum.

2.6.4 Robustness Check: Exchange Rates and CIP Deviations

The exchange rate is an essential variable for the price deviation construction. Since currency may depreciate when there are institutional failures in the country, we need to rule out the role of exchange rate in driving the main results. We first evaluate whether exchange rate changes affect the price deviation. Figure B.13 plots coefficients of univariate regressions of price deviation on lead and lagged exchange rate returns. We find that one-week lagged and simultaneously currency appreciation contribute to the increase in price deviation increase: one bps increase in exchange rate translates into 0.2 bps increase in price deviation. The response shrinks to 0.1 bps with two-week lagged exchange rate returns, and almost zero with more lags. For any shock in exchange rate, about 20% passes into price deviation simultaneously, and takes about two to three weeks to fade away. The relationship itself illustrates the limited arbitrage in cryptocurrency trading.

Do exchange rate impacts contaminate our empirical identifications? The short answer is no. We add currency exchange rate returns and one-week lagged returns to the main specifications in Table B.16. All coefficients basically stay the same in magnitude and statistical significance : from 2.68 (t = 2.71) to 2.69 (t = 2.71) for Google Trend data on the word "Crisis," 5.99 (t = 4.69) to 6.04 (t = 4.70) for return asynchronization, 119.4 (t = 2.75) to 115.3 (t = 2.67) for Bitcoin returns, and 237.8 (t = 2.24) to 223.1 (t = 2.11) for local stock returns. Consistent with Figure B.13, exchange rate returns do positively predict the price deviations, but orthogonal to factors we identify in Section 3.5.

We further explore whether Bitcoin price deviations can predict anything in the currency markets. First, we relate Bitcoin price deviations to the famous covered interest parity (CIP) deviations (Du et al. (2018)). Table B.17 Column (1) reports the univariate regression but fails to identify any relationship with CIP deviations. In Columns (2)-(5), we check whether Bitcoin price deviations predict any currency depreciation or appreciation. We also find no evidence that Bitcoin price deviations predict anything in the future one week, 8 weeks, and 24 weeks. Moreover, a high-rise price deviation does not indicate a higher probability for a fiat currency crisis, defined as a 15% depreciation in the next 24 weeks. Our results imply that Bitcoin price deviations mostly come from the factors that determine Bitcoin demand, but contain little information in FX markets.

2.6.5 Robustness Check: Factors Comparison

This section compares the variables that affect price deviations as documented before. We rank the variables based on their explanatory power in price deviations and argues that factors out-perform in countries with higher levels of distrust. In addition, we investigate whether search on institutional failures and distrust still have prediction power on price deviation after controlling return asynchronization (i.e. friction level) and past returns (i.e. risk appetite).

Based on our analysis, eight factors can explain the variation of price deviations: four Google searches for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for Bitcoin, return asynchronization, past Bitcoin returns, and past local stock market returns.[54] We analyze the R-squared of a set of simple univariate regressions:

$$\widehat{Deviation_{c,t}} = \beta X_{c,t} + \gamma + \epsilon_{c,t}$$

where $\widehat{Deviation_{c,t}}$ is the demeaned price deviation, and $X_{c,t}$ denotes each of the above eight factors.[55] Table B.18 Column (1) reports the in-sample R-squared of the above regressions on the eight factors individually, and we rank the factor performance based on the R-Squared:

$$Asyn_c > Ret^{BTC}_{USD,t-9\to t-1} > GT\_Conflict > GT\_Scandal > GT\_Bitcoin$$
$$> GT\_Crisis > Ret^{Stock}_{c,t-9\to t-1} > GT\_Instability$$

[54] A few papers studied the cryptocurrency trading strategies. See e.g., Griffin and Shams (2019), Liu and Tsyvinski (2018) and Liu et al. (2019).

[55] The demeaned price deviation is the raw deviation minus the country-level average deviation, that is, $\widehat{Deviation_{c,t}} = Deviation_{c,t} - \bar{Deviation}_c$.

Return asynchronization is the leading factor, explaining 2.82% of variation. Among four Google indices on institutional failures, "Conflict" and "Scandal" take the lead by accounting for 1.66% and 1.41%. Past Bitcoin returns, stock market returns, and Google searches for the word "Bitcoin" gain R-Squared of 2.24%, 0.16%, and 0.66%, respectively.

Furthermore, we evaluate the relationship between R-squared and trust for each factor. Table B.18 Columns (2)-(4) show that factors generally out-perform in medium-trust and low-trust countries compared to high-trust countries.[56] On average, each factor only explains 0.49% variation in high-trust countries, but 2.89% and 1.72% in medium and low-trust countries, respectively.

Then, we conduct a multi-factor analysis to evaluate the aggregate performance. Table B.19 reports multi-factor regressions to access the marginal explanatory power of each factor. In addition to return asynchronization, institutional failures contribute an extra 1.11% to R-squared. Bitcoin return raises another 2.24%. Stock market returns add 0.18% to the explanatory power. In total, eight factors capture a 6.35% variation in price deviations. From the table, we also see that after controlling return asynchronization, Google search on "Conflict" and "Scandal" remain positive and highly statistically significant in predicting price deviation.

In high-trust countries, the eight factors jointly explain only 4.02% variation in price deviations, while the aggregate R-squared in medium- and low-trust countries are 14.3% and 8.47%, respectively. Institutional failures matter more in countries with higher distrust: the four Google indices explain 3.07% in low-trust countries, 3.86% in medium-trust countries, but only 0.24% in high-trust countries. Arbitrage frictions matter most in high-trust and medium-trust countries: The return asynchronization alone accounts for 75.6% and 53.4% of the aggregate R-squared (all eight factors combined) in high and medium-trust countries, but only 0.6% in low-trust countries. However, in low-trust countries, institutional failures are more important by 36.2% of the aggregate R-squared.

Lastly, we estimate the time-series R-squared for each country and show that it is negatively correlated with trust. We regress price deviations on eight factors country by country:

$$\widehat{Deviation_t} = \sum_{i=1}^{8} \beta_i X_{i,t} + \gamma + \epsilon_t$$

[56] For example, Google searches for "Crisis" have an explanatory power of 1.35% in low-trust countries, 0.66% in medium-trust countries, and 0.04% in high-trust countries.

Figure B.14 plots the R-Squared against each country's trust level. Across countries, the average explanatory power of the eight factors is around 23.26%.[57] The slope of the fitted line is -13.69% (t = -1.97). The conclusion also holds if we only focus on institutional failures. Figure B.15 plots the explanatory power of the four institutional failure indices in each country versus the trust level. Similarly, the slope of the fitted line is -13.63% (t = -1.86).[58] These factors are better predictors in countries with lower trust levels. Moreover, given the same level of frictions, the R-Squared and coefficients analysis confirms that search on institutional failures and distrust has additional information in price deviation, which in our model captures the excess demand for cryptocurrency.

2.7 Conclusion

Cryptocurrency is often described as a speculative asset with zero fundamental value. We dispute this view and argue that distrust and institutional failures drive the demand for de-nationalized assets. Algorithm trust could be a potent competitor to human trust and establish fundamental value in cryptocurrencies.

Transitory Bitcoin price deviations provide a unique opportunity to investigate determinants of cross-country cryptocurrency demand. We document the limits of arbitrage in cryptocurrency trading: capital controls, limited liquidity, market segmentation, law, and regulations. These frictions prevent arbitragers from adjusting to demand shocks in different countries entirely; thus, the price deviations can sustain.

We integrate trust into a portfolio choice model and highlight that distrust drives heterogeneous price response to demand shocks. Empirical results indicate that price deviations rise as perceived institutional failures increases, Bitcoin and stock markets rally, and arbitrage frictions intensify. Consistent with the model prediction, price responses

[57] Mexico reaches the highest R-Squared by 54.46%, and Romania has a minimum R-Squared of 4.03%. The time-series R-squared would be much higher than R-squared estimated from the panel regressions as it allows country-specific coefficients before factors.

[58] We also conduct parallel analysis for each factor by country in Figure B.16. The average R-Squared across countries are 7.00%, 4.36%, 2.24%, 6.26%, 6.46%, 7.33%, 13.93%, 3.60% for $GT\_Conflict$, GT_Crisis, $GT\_Instability$, $GT\_Scandal$, return asynchronization, past eight-week Bitcoin return, past eight-week stock return, and $GT\_Bitcoin$, respectively. The slopes of the R-Squared on Trust are -10.37% (t = -1.79), -7.98% (t = -1.69), -4.03% (t = -1.84), -7.27% (t = -1.26), -0.18% (t = -0.04), -5.12% (t = -1.19), -1.73% (t = -1.93), and -1.83% (t = -0.60), respectively. The negative correlation between explanatory power and trust holds for almost all factors. The only exception is return asynchronization with a flat fitted line. These findings are broadly consistent with our conclusion—the factors perform better in countries with lower trust.

are augmented in countries with lower trust. Distrust does contribute, at least partially, to cryptocurrency demand.

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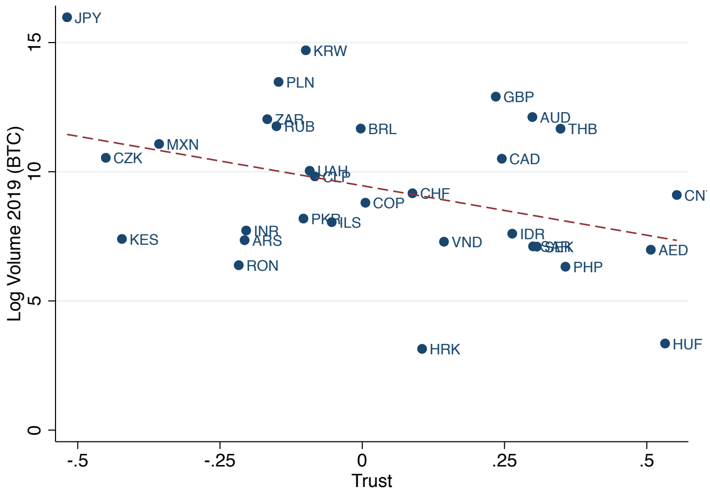
Figures and Tables

Figure 2.1: Bitcoin Trading Volume and Trust Level



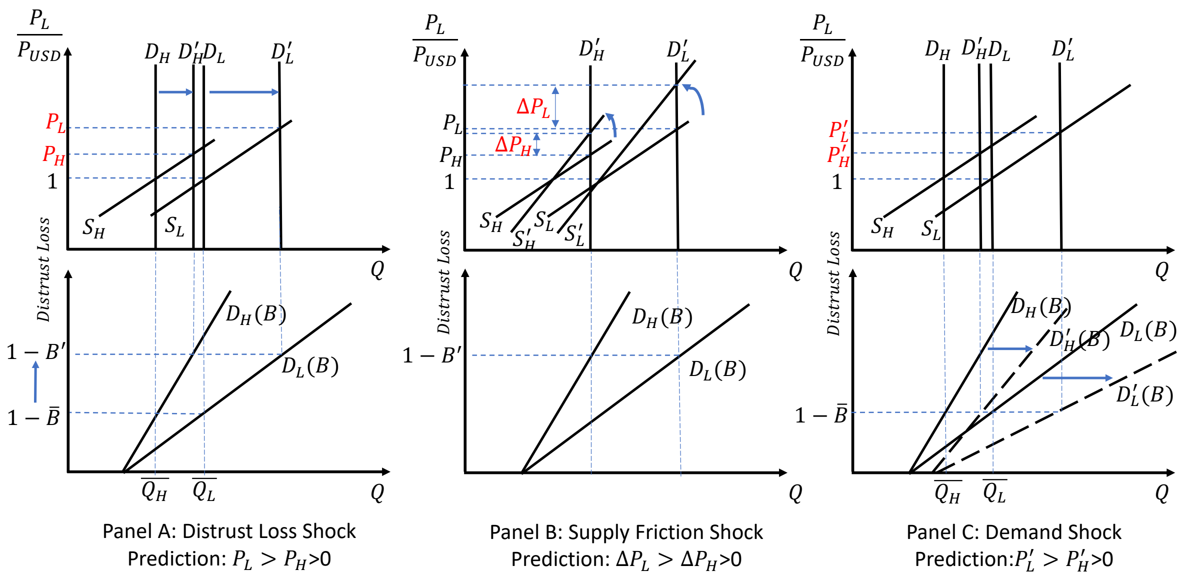
Panel A: Raw Volume

Panel B: Residual Volume

Notes: Panel A plots the relationship between the 2019 log trading volume (in BTC) and the country's trust level. Panel B plots the relationship between the 2019 residual log trading volume (in BTC) and the country's trust level. The residual volume, referring to the volume cannot be explained by population size and GDP, is the error term estimated from the following regression:

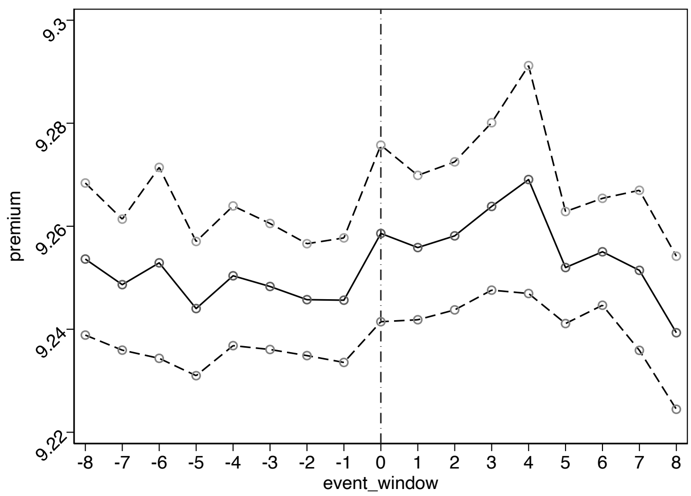
$$Vol_c = \beta_1 Log(Pop_c) + \beta_2 Log(GDP_c) + \widehat{Vol_c}$$

Figure 2.2: Conceptual Framework: Demand and Supply Curve

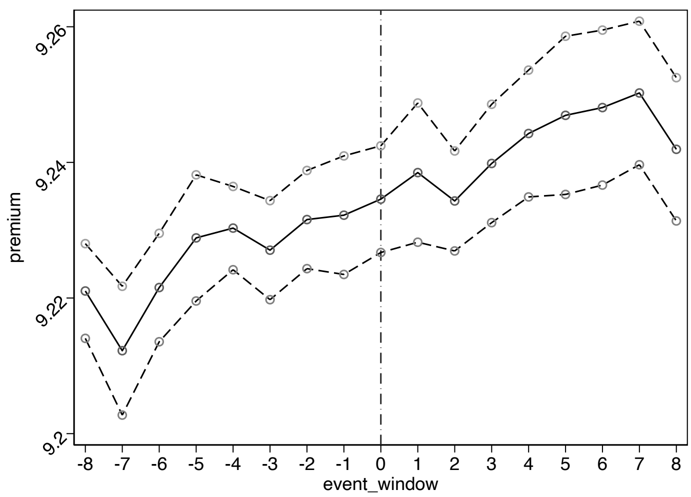


Notes: The top figures are the supply and demand curves that determine the price deviation. The bottom figures are the Bitcoin demand as a function of distrust loss, and the slope captures the country's trust level. We consider two countries only differ by trust, where the demand function of low-trust country $D_L(B)$ yields higher demand for Bitcoin than high-trust country $D_H(B)$, given any positive distrust loss $B > 0$. $\bar{B}$ is the long-run equilibrium distrust level. $\bar{Q_H}$ and $\bar{Q_L}$ represent the long-run equilibrium Bitcoin demand, corresponding to the D_H and D_L in the supply-demand graphs. The supply curves cross the long-run equilibrium with no price deviation: points (D_H, 1) and (D_L,1). Panel A analyzes the distrust loss shock (from $\bar{B}$ to B'), corresponding to Predictions 1 and 2. Panel B studies the increase in arbitrage frictions (supply curves tilt-up), corresponding to Prediction 3. Panel C plots the demand shock driven by risk appetite, which shifts demand function towards the right, corresponding to Prediction 4.

Figure 2.3: Event Study on Google Search Peaks



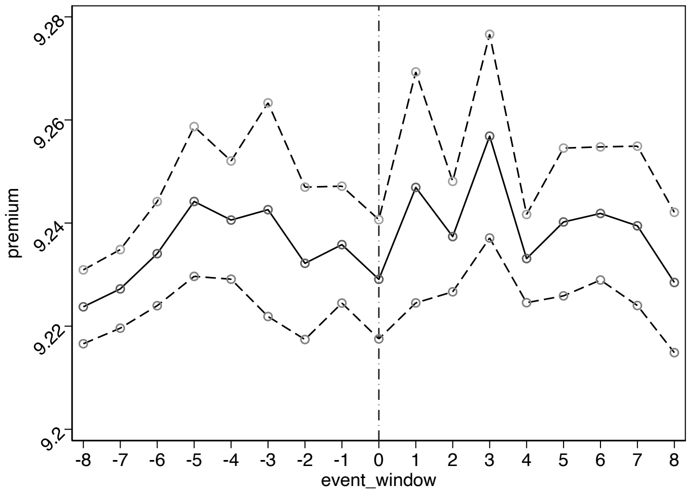
Panel A: Economic Institutional Failures



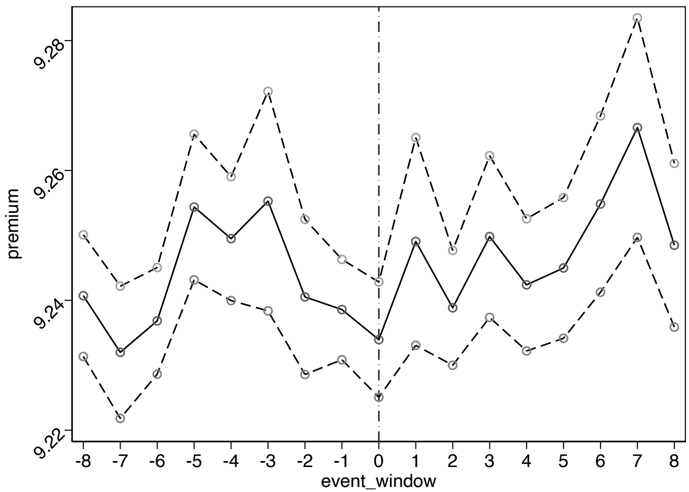
Panel B: Political Institutional Failures

Notes: Panel A plots the event study on economic institutional failures. Panel B plots event study on economic institutional failures.

Figure 2.4: Event Study on Google Search Peaks



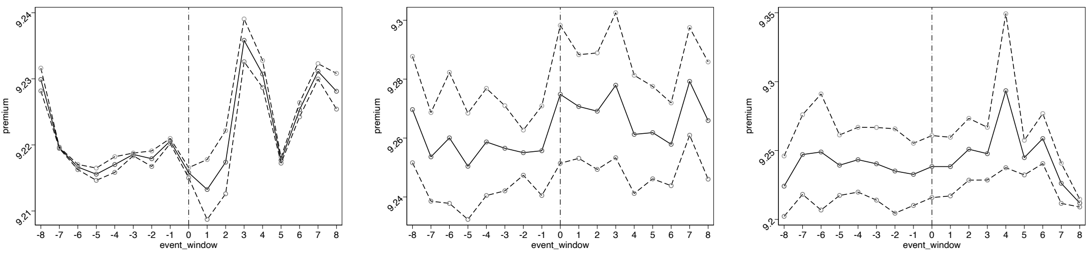
Panel A: Irrelevant Events



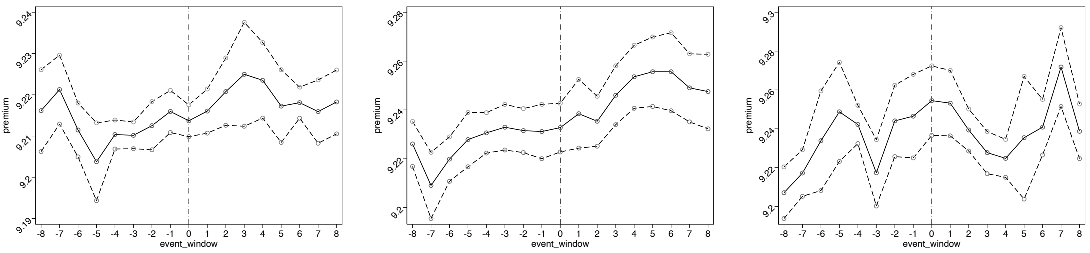
Panel B: Unknown Events

Notes: Panel A plots the event study on irrelevant events. Panel B plots event study on unknown events.

Figure 2.5: Event Study of Economic and Political Institutional Failures by Capital Control Level



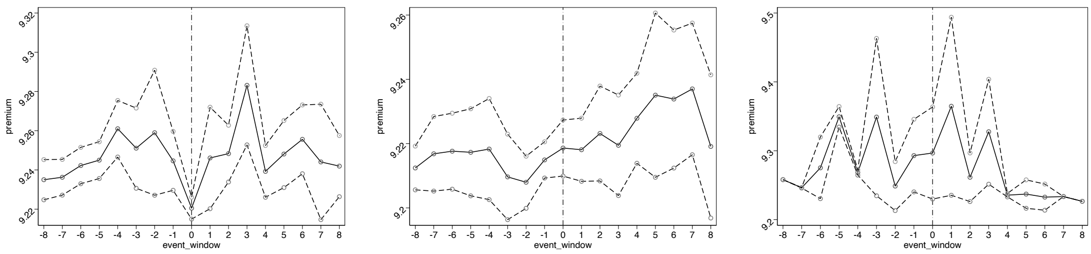
Panel A: Economic Institutional Failures (Open, Gate, Wall)



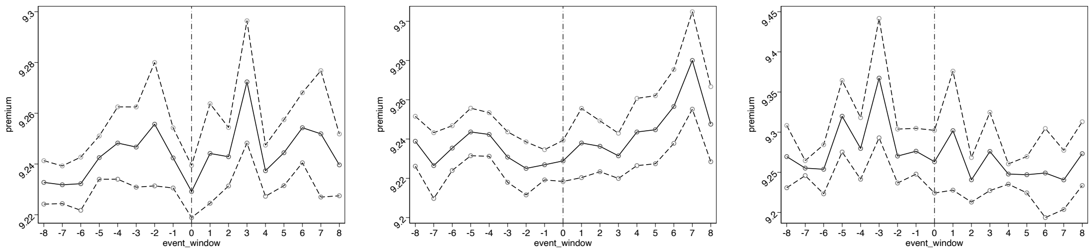
Panel B: Political Institutional Failures (Open, Gate, Wall)

Notes: Panel A plots the event study on irrelevant events. Panel B plots event study on unknown events. To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open (least restrictive), Gate, and Wall (most restrictive).

Figure 2.6: Event Study of Irrelevant and Unknown Events by Capital Control Level



Panel A: Irrelevant Events (Open, Gate, Wall)



Panel B: Unknown Events (Open, Gate, Wall)

Notes: Panel A plots the event study on irrelevant events. Panel B plots event study on unknown events. To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open (least restrictive), Gate, and Wall (most restrictive).

Table 2.1: Bitcoin Trading Volume and Trust Level

	Log Volume (BTC)				Volume (BTC) per capita			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust	-3.829**	-4.718***	-4.347**	-4.861**	-18.03**	-22.14***	-25.02**	-24.85**
	(-2.18)	(-3.58)	(-2.39)	(-2.49)	(-2.06)	(-2.82)	(-2.33)	(-2.31)
Log Pop		1.410***	1.336***	0.738*		4.075**	4.062*	1.309
		(4.31)	(3.77)	(1.75)		(2.09)	(1.94)	(0.56)
Log GDP		1.843***	1.577**	1.197		7.451***	8.521**	3.955
		(4.74)	(2.48)	(1.57)		(3.22)	(2.26)	(0.94)
Legal Status			0.436	0.0338			2.564	0.0857
			(0.59)	(0.04)			(0.58)	(0.02)
Tax Laws			0.323	-0.444			-4.283	-6.468
			(0.31)	(-0.40)			(-0.69)	(-1.06)
Anti-Money Laundering			0.353	-0.133			0.878	-0.745
			(0.73)	(-0.24)			(0.31)	(-0.25)
Capital Controls				-0.0141				-2.594
				(-0.01)				(-0.43)
Credit				0.0169**				0.124***
				(2.21)				(2.95)
R-squared	14.04%	56.67%	58.07%	62.77%	12.73%	37.15%	39.98%	61.45%
# Currencies	31	31	31	28	31	31	31	28

Notes: This table reports the relationship between trust and 2019 Bitcoin trading volume. The independent variable is the 2019 Bitcoin trading volume in Columns (1)-(4), and residual 2019 Bitcoin trading volume per capita in Columns (5)-(8). Columns (1) and (5) are the univariate regressions.

$$Vol_c = \beta Trust_c + \gamma + \epsilon_c$$

Columns (2) and (6) include log population and log GDP per capita in 2016 as covariates. Columns (3) and (7) control the country's cryptocurrency regulations: legal status, tax laws, and anti-money laundering regulations. Columns (4) and (8) further add capital controls and credit by the financial sector (% GDP) to the regression. Three countries are missing in Columns (4) and (8): the United Arab Emirates and Croatia do not have data in capital controls. Canada does not provide credit data in World Development Indicators.

Table 2.2: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	S.D.	25^{th} Percentile	Median	75^{th} Percentile	Obs.
Panel A: Crypto Trading Data						
$Deviation$	10326.32	1325.186	9978.1	10149.1	10524.73	7843
$LogVolume$	5.59	3.07	3.42	5.04	7.76	7843
$Asyn_c$	24.67	29.33	2.84	12.76	36.64	7843
$Ret^{BTC}_{USD,t-9\to t-1}$	0.174	0.41	-0.084	0.079	0.336	7843
Panel B: Stock and Currency Returns						
$Ret^{Stock}_{c,t-9\to t-1}$	0.0134	0.1098	-0.0235	0.0117	0.0455	7843
$Ret^{Currency}_{c,t-9\to t-1}$	0.00398	0.0384	-0.0126	0.0001	0.0197	7843
Panel C: Google Search Data						
$GT\_Conflict$	185.3	67.65	128.96	184.16	232.01	8096
GT_Crisis	144.53	61.07	102.24	141.15	183.37	8096
$GT\_Instability$	130.36	71.28	77.64	116.25	173.87	8096
$GT\_Scandal$	164.39	56.64	126.52	160.78	201.36	8096
$GT\_Bitcoin$	105.46	38.68	82.59	98.74	118.52	7936
$GT\_Ethereum$	112.11	90.69	71.43	95.24	129.03	7786
Panel D: Country Feature						
Trust (GPS)	0.0327	0.293	-0.167	-0.00269	0.299	31
Most People Trusted (WVS)	25.58	15.67	12.2	23.1	33.3	28
Corruption in Business	-5	38.1	-31.9	-11	24.3	17
Corruption in State	-12.11	56.92	-55.9	-33.2	37.4	17
Confidence in Bank	12.92	62.51	-46.95	-1.2	77.8	20
Confidence in Companies	-14.2	36.61	-46.1	-27.6	10.7	27
Confidence in Government	-14.94	68.65	-65.5	-22.5	20.4	27

Notes: Summary statistics. Panel A summarizes Bitcoin trading data: price deviation, trading volume, return asynchronization, and return. Panel B summarizes stock and FX currency returns. Panel C summarizes Google search in keywords of "Conflict," "Crisis," "Instability," "Scandal," "Bitcoin," and "Ethereum". Panel D reports country-level features: trust scores, perceived corruption control, and confidence in various institutions.

Table 2.3: Event Study on Price Deviation

	Dependent Variable: *Deviation* (bps)			
	(1) Economic	(2) Political	(3) Irrelevant	(4) Unknown
Post	0.009*	0.014***	0.004	0.003
	(1.81)	(4.17)	(0.85)	(0.81)
# observations	360	1,460	552	901

Notes: This table reports the four event studies on price deviation: economic institutional failures in Column (1), political institutional failures in Column (2), irrelevant events in Column (3), and unknown events in Column (4).

$$Deviation_{c,t} = \beta Post_{c,t} + \epsilon_{c,t}$$

t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.4: Event Study on Price Deviation by Capital Control

	Dependent Variable: *Deviation* (bps)			
	(1) Economic	(2) Political	(3) Irrelevant	(4) Unknown
Post	0.002	0.012	0.005	0.021**
	(0.11)	(1.24)	(0.39)	(2.07)
Post $\times$*Control*	0.003	0.001	-0.000	-0.010*
	(0.49)	(0.22)	(-0.08)	(-1.75)
# observations	360	1,460	552	901

Notes: This table reports the four event studies and their heterogeneity across countries of different capital control level on price deviation: economic institutional failures in Column (1), political institutional failures in Column (2), irrelevant events in Column (3), and unknown events in Column (4). To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open (least restrictive), Gate, and Wall (most restrictive).

$$Deviation_{c,t} = \beta_1 Post_{c,t} + \beta_2 Control_c \times Post_{c,t} + \epsilon_{c,t}$$

t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.5: Price Deviation Response to Institutional Failures

	Dependent Variable: *Deviation* (bps)			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	2.678**	1.323**	2.133**	2.006***
	(2.71)	(2.07)	(2.38)	(2.81)
One-sd move in Google (%)	1.74	0.78	1.44	1.10
# observations	7,843	7,843	7,843	7,843

Notes: This table reports panel regressions of price deviation on cumulative Google keyword search indices: "Conflict" in Column (1), "Crisis" in Column (2), "Instability" in Column (3), "Scandal" in Column (4).

$$Deviation_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.6: Attention to Bitcoin and Trading Volume

	Panel A: Dependent Variable $\Delta GT\_Bitcoin_t$			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	0.100***	0.105***	0.0514**	0.0308**
	(4.52)	(4.68)	(2.68)	(2.62)
# observations	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $\Delta Volume$			
Google Trend Index	0.111***	0.0905**	0.0256	0.0904***
	(3.31)	(2.29)	(0.86)	(2.85)
# observations	7,752	7,752	7,752	7,752

Notes: This table reports the impact of institutional failures on attention to Bitcoin and trading volume. In Panel A, the dependent variable is growth in "Bitcoin" Google searches $\Delta GT\_Bitcoin_t = \frac{8 \times GT\_Bitcoin_t}{\sum_{i=1}^{i=8} GT\_Bitcoin_{t-i}}$. In Panel B, the dependent variable is trading volume growth $\Delta Volume = log(\frac{8 \times Vol_t}{\sum_{i=1}^{i=8} Vol_{t-i}})$. The independent variable is cumulative Google keyword search indices: "Conflict" in Column (1), "Crisis" in Column (2), "Instability" in Column (3), "Scandal" in Column (4).

$$\Delta GT\_Bitcoin_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7: Price Deviation Response to Google Trend by Trust

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
GT_Crisis	2.678**	-0.309	4.522**	4.587*	-5.469**
	(2.71)	(-0.47)	(2.70)	(2.00)	(-2.32)
GT_Crisis × *Distrust*					8.530***
					(2.95)
# observations	7,843	2,783	2,277	2,783	7,843
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price response to the Google searches of the keyword "Conflict" and its heterogeneity by the trust. High-trust countries in Column (2) refer to 11 countries with GPS trust score above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries in Column (4) refer to 11 countries with a trust score below -0.1. Column (5) reports the heterogeneous response by trust level:

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. $Distrust_c$ is omitted as currency fixed effects fully absorb it. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.8: Price Deviation Response to Market Friction

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Asyn_c$	8.548***	4.267***	7.625*	13.92***	-2.100
	(4.35)	(3.73)	(1.94)	(3.35)	(-0.57)
$Asyn_c \times Distrust$					0.11**
					(2.20)
Mean $Asyn_c$	30.02%	30.37%	31.32%	28.65%	30.02%
S.D $Asyn_c$	32.77%	33.41%	32.98%	31.88%	32.77%
# observations	10,705	3,903	3,000	3,802	10,705

Notes: This table reports the price response to the return asynchronization and its heterogeneity by the trust. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Asyn_{c,t} + \beta_2 Distrust_c \times Asyn_{c,t} + \gamma_c + \epsilon_{c,t}$$

Table 2.9: Price Deviation Response to Bitcoin Return

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Ret^{BTC}_{USD,t-9\to t-1}$	1.194**	0.434	1.555	1.658**	-1.816
	(2.75)	(0.55)	(1.75)	(2.76)	(-1.17)
$Ret^{BTC}_{USD,t-9\to t-1} \times Distrust$					3.111**
					(2.15)
# observations	8,060	2,860	2,340	2,860	8,060
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price response to past eight-week Bitcoin returns and its heterogeneity by the trust. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Ret^{BTC}_{USD,t-9\to t-1} + \beta_2 Distrust_c \times Ret^{BTC}_{USD,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

Table 2.10: Price Deviation Response to Local Stock Return

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Ret^{Stock}_{c,t-9\to t-1}$	2.378**	-1.318	1.886	8.000***	-7.981
	(2.24)	(-0.45)	(1.83)	(3.83)	(-1.33)
$Ret^{Stock}_{c,t-9\to t-1} \times Distrust$					10.49*
					(1.77)
# observations	8,060	2,860	2,340	2,860	8060
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price response to the past eight-week domestic stock return and its heterogeneity by the trust. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Ret^{Stock}_{c,t-9\to t-1} + \beta_2 Distrust_c \times Ret^{Stock}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

Table 2.11: Distrust Loss Elasticity Estimation

	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Elasticity χ	0.621**	0.474	0.580*	0.329
	(2.20)	(1.40)	(1.99)	(0.78)
# observations	7,843	7,843	7,843	7,843

Notes: This table reports distrust loss elasticity χ estimated from the following quasi-triple difference-in-difference specification:

$$\begin{aligned} Deviation_{c,t} =& \beta_1 Asyn_{c,t} + \beta_2 \lambda Asyn_{c,t} \times Distrust_c + \beta_3 GT_{c,t} + \beta_4 GT_{c,t} \times Asyn_{c,t} \\ &+ \chi GT_{c,t} \times Asyn_{c,t} \times Distrust_c \gamma_c + \epsilon_{c,t} \end{aligned}$$

$GT_{c,t}$ refers to "Conflict" in Column (1), "Crisis" in Column (2), "Instability" in Column (3), "Scandal" in Column (4). $Distrust_c$ is omitted as currency fixed effects are included. Robust standard errors are clustered at currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

The Evolution of Market Beliefs

I construct a measure which captures the evolution of market beliefs based on option data. By tracking market belief updates over time, I find evidence of excess volatility in expected returns in one-month investment horizons. The evidence is inconsistent with expected returns being a martingale. I find no evidence of excess volatility in six-month investment horizons. Based on the dynamics of market beliefs, I measure uncertainty as the time-series volatility of expected returns. I show evidence of an uncertainty premium.

JEL-Classification: G10, G12, G17.

Keywords: Market Beliefs, Expected Return, Excess Volatility, Uncertainty, Option Term Structure

3.1 Introduction

How does investor learning affect expected return volatility? Under the assumption that the discount rate is constant, Shiller (1981) shows that stock prices are too volatile compared to future cash flows. Most explanations for the excess volatility puzzle focus on time-varying discount rates. However, investor beliefs are not observable; tracking belief updates when more information becomes available is difficult. In this paper, I propose a new way to measure changes in market beliefs about expected returns. The measure uses forward-looking information reflected in the term structure of options. Using this measure, I provide evidence on how the learning process affects uncertainty and expected return fluctuations.

I use a different approach from that of the literature that uses macroeconomic and financial variables to proxy for market beliefs and economic uncertainty. Based on an estimate of the expected return on the market by Martin (2017) and Martin and Wagner (2018), I propose a new measure that captures the evolution of market beliefs and their uncertainty using forward-looking information from option prices. The measure provides a time-series estimate of expected returns for a future fixed time interval, making the evolution of market beliefs about expected returns observable. I use option prices with different maturities to estimate the term structure of expected returns on the market and individual stocks, which allows me to construct a time series of expected returns over a fixed future time interval. I track market belief updates for option prices from the time series. The measure gives me an estimation of the magnitude of returns, which is easy to interpret.

I analyze short-term and long-term market belief dynamics for two investment horizons (one month and six months). For the one-month investment horizon, I obtain market belief updates for the past six months, while for the six-month investment horizon, I use data from the past two years. I consider both the level and the change (i.e. unexpected shocks) of market beliefs. By tracking market belief updates over time, I find that market beliefs evolve differently over different investment horizons. For one-month investment horizons, investors can forecast future expected returns more accurately initially; noise increases with time. For six-month investment horizons, I find the opposite result. There is time-series excess volatility over six-month horizons. Overall, the findings suggest that the expected return process is not a martingale, at least not in the short run. As my results may have in-sample biases, I also conduct out-of-sample tests. I obtain more than 5 per cent and 20 per cent out-of-sample R-squares for the one-month and six-month investment horizons, respectively.

To the best of my knowledge, I am the first to provide a model-free estimate of expected return volatility. Based on the dynamics of market beliefs, I construct an uncertainty measure, $UVIX$, which considers belief changes. In particular, I use the standard deviation of the time-series return estimates. In addition, as an alternative measure, I perform a principal component analysis to obtain the first two principal components capturing most of the variation in market beliefs.

A key advantage of my measure is that it is high-frequency and forward-looking. I can measure uncertainty daily using option markets data. I show that $UVIX$ is highly correlated with the market risk premium and that it captures an economically large and statistically significant uncertainty premium. My measure differs from $SVIX$ and VIX, as I measure the changes in market beliefs over time, capturing a different dimension of uncertainty. The uncertainty measure is based on the standard deviation of investor beliefs over the same time interval at different points in time. My empirical tests show that the second moment of the market belief measure contains different information from that in VIX.

In addition, I obtain preliminary results for individual stocks using the same procedure. Standard cross-sectional tests show that investors face more noise when estimating the expected return on a stock than when estimating the expected return on the market. I also construct an uncertainty measure for each individual stock and find consistent results with those for market returns: the measure of uncertainty has a striking relationship with the expected return over the fixed time interval.

My paper makes three key contributions. First, I provide a novel way to track the evolution of market beliefs about expected returns over a future fixed time interval. While Martin (2017) and Martin and Wagner (2018) construct measures capturing the expected return from time 0 to T, I create a novel measure that captures the expected return from time T to T+1. Meanwhile, from time 0 to T-1, my measure gives T-1 estimates of expected returns for the same time interval, T to T+1. Thus, market belief updates can be tracked model-free and survey-free. Second, I show excess volatility evidence suggesting that the expected return process is not a martingale. Investors can forecast expected returns over a future fixed time interval more accurately at first, while there is more noise as time goes by. This excess volatility finding contributes to the literature on excess volatility of stock prices and cashflows, which provides another aspect to investigate in further research. For example, information from excess volatility in expected returns can be extracted to find additional return and risk factor predictors. Finally, I construct a robust new measure of uncertainty, $UVIX$, based on the uncertainty embedded in the evolution of market beliefs, which is different from existing measures of stock market volatility such as VIX. The uncertainty comes from the volatility of investors' beliefs over the same time interval at other time points. The second moment of the market belief measure contains different information from VIX, as is shown in the empirical tests. According to my knowledge, I am the first to empirically measure market belief evolution over time and quantify the uncertainty embedded in the learning process of market participants. My work provides empirical evidence that can speak to the theoretical mechanism of how market beliefs evolve over time and why there is excess volatility in short-term belief paths.

Following Shiller (1979) and Shiller (1981), there is a strand of literature related to excess volatility. LeRoy and Porter (1981) investigate the implications for asset price dispersion of conventional security valuation models. De Bondt and Thaler (1985) study market efficiency that investigates whether the behavior of overreacting affects stock prices. Campbell and Shiller (1987) test excess volatility in asset prices relative to rational expectations theory. LeRoy and LaCivita (1981) document that volatility tests based on models assuming risk neutrality will generate downward-biased estimates of implied price variances. Kleidon (1986) and Marsh and Merton (1987) emphasize that it is important to take into consideration non-stationarity for excess volatility. Giglio and Kelly (2017) use term structure analysis to find excess volatility in long-term maturity claims compared to short-term maturity claims. The excess volatility cannot be explained by discount rates. They propose five explanations: omitted factors, non-linear dynamics, long-memory dynamics, measurement error, and temporary mispricing of long maturity claims. Augenblick and Lazarus (2018) address the question of how restrictive the assumption of rational expectations in asset markets is. They map the variation in risk-neutral probabilities of future outcomes and the minimum curvature of utility and show that overreaction is strongest for belief over prices at distant horizons.

A strand of literature is about eliciting forward-looking information on expected returns from option prices (Martin (2018)). Breeden and Litzenberger (1978), Ross (2015), Martin and Ross (2019), and Borovička et al. (2016) show that the physical probability distribution of returns can be recovered, but the regularity condition on the stochastic discount factor may not be realistic. To tackle this problem differently, Martin (2017) derive a lower bound for expected returns from option prices and show that the lower bound is tight. Under mild assumptions, the $SVIX$ index is proved to be a good proxy of the expected return on the market. Following this approach, Martin and Wagner (2018), Kremens and Martin (2019), and Kadan and Tang (2019) further work on the expected return on individual stocks and foreign exchange markets, providing important insights and robust results. They have shown that the methodology of eliciting information about expected returns from risk-neutral variances works well in different markets and for various asset classes. My results contribute to estimating the evolution of market beliefs. They also provide an alternative measure of uncertainty. Martin (2017) discusses the term structure of equity premia. Still, his focus is to decompose the long-horizon equity premium as a weighted average of forward equity premia, exactly analogous to the relationship between spot and forward bond yields. In this paper, I focus on market belief updates over a fixed future time interval and look at the term structure of options over time.

My paper is related to the previous literature on uncertainty. Bloom (2014) discusses some facts and patterns about economic uncertainty and addresses questions about fluctuations in uncertainty during business cycles and their effects on behavior. Baker et al. (2016) develop a new index of economic policy uncertainty based on newspaper coverage frequency. Manela and Moreira (2017) construct a text-based measure of uncertainty using the front page of The Wall Street Journal. Bachmann et al. (2013) construct time-varying business uncertainty measures using survey expectations data and analyze their impact on economic activity. Jurado et al. (2015) provide new measures of uncertainty and employ alternative econometric estimates of uncertainty. Drechsler (2013) constructs an equilibrium model capturing the properties of index option prices, equity returns, variance, and the risk-free rate, which shows that time variation in uncertainty generates fluctuations in the variance premium and helps explain the predictability of stock returns.

Bloom (2009) offers a structural framework to analyze the impact of uncertainty shocks based on a model with a time-varying second moment. Hansen and Sargent (2019) derive a model to describe prices of macroeconomic uncertainty that emerge from how investors evaluate consequences of alternative specifications of state dynamics. My measure of uncertainty is clearly different, as it directly measures the changes in market beliefs in expected returns over time.

The paper is organized as follows. Section 3.2 describes the theoretical motivation and the methodology. Section 3.3 discusses the data, the evolution of the market beliefs, and the excess volatility findings. Section 3.4 presents the results of out-of-sample tests. Section 3.5 shows that the uncertainty measure $UVIX$ is correlated with equity risk premia and that there is an uncertainty premium. Section 3.6 presents the analysis of individual stocks. Section 3.7 concludes.

3.2 Theoretical Motivation

3.2.1 Excess Volatility

Investors form their beliefs about future expected returns as they learning about the market. Market beliefs are time-varying as economic conditions change over time and market participants adjust their beliefs when incorporating new information. They learn about good and bad news in good times and bad times and adjust their beliefs accordingly. Since economic conditions change, investors form and update their beliefs frequently.

Investors at different points in time (say, t and $t+1$) have different beliefs about the expected return at time T, and such beliefs also change over time. Consider a time-series of expected returns over the same time interval:

$$E_t(R_T), E_{t+1}(R_T), E_{t+2}(R_T), ..., E_{T-1}(R_T) \tag{3.1}$$

By the law of iterated expectation, the expected return is a martingale. In particular:

$$E_{t+1}(R_T) - E_t(R_T) = \epsilon_{t+1} \tag{3.2}$$

$$Cov(\epsilon_{t+1}, E_t(R_T)) = E_t(\epsilon_{t+1} E_t(R_T)) = E_t E_{t+1}(\epsilon_{t+1} E_t(R_T)) = E_t(R_T) E_t(\epsilon_{t+1}) = 0 \tag{3.3}$$

The following equation should also hold:

$$Var(E_{t+k}R_T) = E(Var_t(E_{t+k}R_T)) + Var(E_t(E_{t+k}R_T)) \tag{3.4}$$

Since

$$E(Var_t(E_{t+k}R_T)) \geq 0, \tag{3.5}$$

we have that

$$Var(E_t(E_{t+k}R_T)) \leq Var(E_{t+k}R_T), \tag{3.6}$$

that is,

$$Var(E_t(R_T)) \leq Var(E_{t+k}R_T). \tag{3.7}$$

I proposed a novel way to estimate the quantities in (3.1) empirically using option data, from which I can see how the information at different time points is related to future realized excess returns. In particular, I use the term structure of options to construct a forward $SVIX$ that captures information about forward expected returns at the same time interval. After constructing the measure, I also consider the uncertainty of market beliefs. According to the theory, expected returns should be a martingale. Therefore, when market participants form their beliefs about expected returns, their learning should reduce uncertainty and attenuate asset price fluctuations. Moreover, I can also test whether variances differ at different stages of belief formation. My work is related to Shiller (1981), who argues that because conditional expectations are less volatile than realizations, stock prices should be less volatile than realized cash flows. However, Shiller (1981) provides empirical evidence of significant excess volatility. I am interested in whether there is excess volatility in market beliefs. If there is, I can extract information from the evolution of market beliefs to estimate the uncertainty premium.

3.2.2 Expected Returns

Martin (2017) and Martin and Wagner (2018) propose proxies for the expected returns on the market and individual stocks under mild assumptions, and show that their measures perform well empirically. I assume that their forward-looking measure is unbiased and use it to proxy for expected returns. Based on their setting, I define three different measures of risk-neutral variance:

$$SVIX^2_{t\to T} = var^*_t(R_{m,t\to T}/R_{f,t\to T}) \tag{3.8}$$

$$SVIX^2_{i,t\to T} = var^*_t(R_{i,t\to T}/R_{f,t\to T}) \tag{3.9}$$

$$\overline{SVIX}^2_{t\to T} = \sum_i w_{i,t} SVIX^2_{i,t\to T} \tag{3.10}$$

Martin (2017) introduces the $SVIX^2_{t\to T}$ index, which can be directly computed from index option prices. Motivated by this, Martin and Wagner (2018) introduced the stock-level $SVIX^2_{i,t\to T}$ index, and the $\overline{SVIX}^2_{t\to T}$ index that measures average stock volatility. $R_{m,t\to T}$ denotes the return on the market index from time t to T, and $R_{i,t\to T}$ denotes the return on individual stocks i in the market index. $w_{i,t}$ is the weight of stock i in the market index at time t according to its market capitalization. var^*_t denotes the risk neutral variance at time t.

Following the approach of Breeden and Litzenberger (1978), I compute the risk-neutral variance terms in the above equations. The procedure is standard in the literature, so I omit the details of the derivations here. The indices can be computed using the following formulas:

$$SVIX^2_{t\to T} = \frac{2}{R_{f,t\to T} S_{m,t}}[\int_0^{F_{m,t\to T}} put_{m,t\to T}(K)dK + \int_{F_{m,t\to T}}^{\infty} call_{m,t\to T}(K)dK] \tag{3.11}$$

$$SVIX^2_{i,t\to T} = \frac{2}{R_{f,t\to T} S_{i,t}}[\int_0^{F_{i,t\to T}} put_{i,t\to T}(K)dK + \int_{F_{i,t\to T}}^{\infty} call_{i,t\to T}(K)dK] \tag{3.12}$$

Based on these formulas, I use the data from Option Metrics to do the computation directly. $S_{m,t}$ and $S_{i,t}$ denote the spot prices of the market index and the individual stock, and $F_{m,t\to T}$ and $F_{i,t\to T}$ denote the forward prices of the market index and the individual stock, respectively. $call_{m,t\to T}$ and $put_{m,t\to T}$ are the price of European call and put options on the market index at time t with the expiration date at time T. $call_{i,t\to T}$ and $put_{i,t\to T}$ denote the prices where the underlying assets are individual stocks i. With the stock-level index, I compute the weighted average to obtain $\overline{SVIX}^2_{t\to T} = \sum_i w_{i,t} SVIX^2_{i,t\to T}$. $w_{i,t}$ can be calculated for each trading day using the number of shares outstanding and stock price data at time t for each i. I use the index constituent dataset to keep the stocks in the market index in every trading day, and compute the weight by using the total market capitalization of the market index as a sum of all the stocks at time t.

After obtaining the indices, I estimate the expected returns on the market and stocks according to Martin (2017) and Martin and Wagner (2018). They prove that under the negative correlation condition (NCC), which holds under different theoretical settings, there is a particular relationship between expected returns and the risk-neutral variance. They further show that the lower bound is tight and their estimates of expected returns work well empirically. I follow their approach to estimate expected returns. Particularly, the equations for estimating expected returns are as follows:

$$\frac{1}{T-t}(E_t R_{m,t\to T} - R_{f,t\to T}) = R_{f,t\to T} SVIX^2_{t\to T} \tag{3.13}$$

$$\frac{1}{T-t}(E_t R_{i,t\to T} - R_{f,t\to T}) = R_{f,t\to T} SVIX^2_{t\to T} + \frac{1}{2} R_{f,t\to T}(SVIX^2_{i,t\to T} - \overline{SVIX}^2_{t\to T}) \tag{3.14}$$

Based on the above equations, I produce time series of expected returns on the market and individual stocks for different investment horizons using options of different maturities. I focus on 1-month, 2-month, 3-month, 4-month, 5-month, and 6-month horizons for the analysis of short-term belief evolution, and 6-month, 12-month, 18-month, and 24-month horizons for the analysis of long-term belief evolution.

3.2.3 Methodology

The key component of my measure is the information reflected in the term structure of options, which is informative about investors' beliefs. Based on Martin (2017) and Martin and Wagner (2018), I use option prices with different maturities to obtain estimates of the term structure of the expected returns on the market and stocks, which allows me to estimate a time-series of expected returns over a fixed future time interval. Fixing the time interval and moving along time allows me to obtain time-series estimates of the same return. From the time series, I can track market belief updates for the time-series of option prices.

Assume the current time is T_0. Let $MB^{T_i}_{T_0}$ denote the market belief about expected returns based on option prices at time T_0 for options that expire at time T_i. Assuming that the option price data only contain information over its lifespan, then $MB^{T_i}_{T_0}$ contains information from time T_0 to T_i. From equation 3.13 and 3.14, the market belief about expected returns on the market and on an individual stock are as follows:

$$MB_{T_0}^{T_i} = R_{f,T_0\to T_i} SVIX^2_{T_0\to T_i} \tag{3.15}$$

$$StockMB_{T_0}^{T_i} = R_{f,T_0\to T_i} SVIX^2_{T_0\to T_i} + \frac{1}{2} R_{f,T_0\to T_i}(SVIX^2_{j,T_0\to T_i} - \overline{SVIX}^2_{T_0\to T_i}) \tag{3.16}$$

As I want to analyze changes in market beliefs at different points in time, I fix the time interval and consider the information from the same time interval at different times. I define the forward MB as the forward market belief about expected returns. Consider two future time points $T_1 < T_2$. The forward MB is defined as

$$MB_{T_0}^{T_1,T_2} = MB_{T_0}^{T_2} / MB_{T_0}^{T_1} \tag{3.17}$$

$MB_{T_0}^{T_1,T_2}$ only contains information embedded in the options from time T_0 to T_2, but not in the options from time T_0 to T_1. Thus, for the fixed time interval from T_1 to T_2, I use options starting at different T_0 to track changes in market beliefs at different points in time. Therefore, I use information from the option term structure to obtain a term structure of MB. The forward $MB_{T_0}^{T_1,T_2}$ should predict the market and stock returns from time T_1 to T_2.

I construct measures of two investment horizons: 1-month horizon (short term) and 6-month horizon (long term). I use the short-term measure to illustrate how I construct the measure. Suppose that we want to estimate the expected return over a fixed time interval $t-1$ to t. We can have 6 forward MB to measure the same return at different points in time: $MB_{t-1}^{0,1}$, $MB_{t-2}^{1,2}$, $MB_{t-3}^{2,3}$, $MB_{t-4}^{3,4}$, $MB_{t-5}^{4,5}$, and $MB_{t-6}^{5,6}$. These measures are the investors' beliefs about the expected return $E(R_t)$ in the past 6 months, where in each month I can track the market belief about the same return. Note that $MB_{t-6}^{5,6}$ is the first and the earliest market belief and $MB_{t-1}^{0,1}$ is the last and the latest market belief. Figure 3.1 illustrates how I construct the market belief measure graphically.

3.3 Evolution of Market Beliefs and Excess Volatility

I propose two ways to capture unexpected changes in market beliefs about future expected returns. The first measure is the difference between $MB_{t-i}^{T_1,T_2}$ and $MB_{t-i-1}^{T_2,T_3}$.

Intuitively, the larger this change is, the higher the uncertainty. In addition, positive and negative changes with the same absolute value have different interpretations, which may reflect bullish or bearish markets.

The second measure is based on a regression. I use the residuals from the regression of $MB_{t-i}^{T_1,T_2}$ on $MB_{t-i-1}^{T_2,T_3}$ as unexpected shocks to market beliefs. This method is standard in the existing literature. In the two subsections below, I discuss the results for short-term and long-term belief changes.

3.3.1 Data

I obtain daily data from Option Metrics for S&P 500 index options and the individual stocks in the S&P 500 index, which can be downloaded from WRDS. This dataset contains time-series of implied volatility surface data from January 1996 to December 2017. Each underlying asset has multiple call and put options of different strike price and maturities. I infer (from calculations) implied strike prices and implied option premiums. On each day, I also have closing prices of all available options with different underlying assets from Option Metrics. For the market index and each stock, I take the options with maturities of 30, 60, 91, 122, 152, 182, 365, 547, 730 calendar days, which is corresponding to 1, 2, 3, 4, 5, 6, 12, 18, 24 months to construct my measure. The volatility surface data contain options with delta 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80 (for put options, the deltas are negative). For individual stocks, I focus on the stocks that were in the S&P 500 index starting from January 1996. To get the index constituents, I follow the standard procedure using Compustat index constituent data. The dataset specifies the period that each stock is in the index, so that I can get a set of stocks in the index on a daily basis, that is, every day I have a set of stocks that are in the S&P 500 index. Daily price and return data are obtained from CRSP. I also get number of shares outstanding and firm characteristics from Compustat. I merge the Option Metrics data with Compustat and CRSP data to get my dataset for measure construction and further analysis.

3.3.2 Short-term Belief Evolution

In this subsection, I discuss the short-term market belief evolution, which is corresponding to the fixed 1-month investment horizon. Denote the first and earliest market belief $MB^{5,6}_{t-6}$ as $MB_{1,t}$, followed by $MB^{4,5}_{t-5}$ as $MB_{2,t}$, $MB^{3,4}_{t-4}$ as $MB_{3,t}$, $MB^{2,3}_{t-3}$ as $MB_{4,t}$, $MB^{1,2}_{t-2}$ as $MB_{5,t}$, and $MB^{0,1}_{t-1}$ as $MB_{6,t}$. Figure 3.2 shows the market belief about expected returns for the 1-month investment horizon. From these measures, I run the following regressions:

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MB_{i,t} + \epsilon_{i,t} \tag{3.18}$$

$$R_{m,t}-R_{f,t} = \beta_{0,t}+\beta_{1,t}MB_{1,t}+\beta_{2,t}MB_{2,t}+\beta_{3,t}MB_{3,t}+\beta_{4,t}MB_{4,t}+\beta_{5,t}MB_{5,t}+\beta_{6,t}MB_{6,t}+\epsilon_t \tag{3.19}$$

For the above equations, $i = 1, 2, 3, 4, 5, 6$. Table 3.1 reports the results. There are 5432 observations from 1996 to 2017. The table confirms the results of Martin (2017). Specifically, $MB_{6,t}$ here is the measure proposed by Martin (2017). The coefficient is 0.837, which is very close to and not significantly different from 1. When all 6 measures are included in the same regression, I find that there is a large variation, with different signs across time. This finding indicates that market belief about expected returns may capture an uncertainty premium.

Table 3.2 and Table 3.3 show how market beliefs about expected returns evolve over time. The tables show the relationship between excess returns and market belief changes. The market belief change also captures the uncertainty about future expected returns. A bigger change means higher uncertainty. Note also positive changes contain different information from negative changes. A large positive change suggest that investors believe that the market will improve, while large negative change indicates the opposite. The regressions in Table 3.2 and Table 3.3 are:

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MBC^{x}_{i,t} + \epsilon_{i,t} \tag{3.20}$$

$$R_{m,t}-R_{f,t} = \beta_{0,t}+\beta_{1,t}MBC^{x}_{1,t}+\beta_{2,t}MBC^{x}_{2,t}+\beta_{3,t}MBC^{x}_{3,t}+\beta_{4,t}MBC^{x}_{4,t}+\beta_{5,t}MBC^{x}_{5,t}+\beta_{6,t}MBC^{x}_{6,t}+\epsilon_t \tag{3.21}$$

For the above equations, $i = 1, 2, 3, 4, 5, 6$ and $x = d, r$. $MBC^{d}_{i,t}$ and $MBC^{r}_{i,t}$ are unexpected changes in market beliefs based on the difference and regression methods, respectively. Specifically, for $i = 2, 3, 4, 5, 6$ and $x = d, r$, they are as follows:

$$MBC^x_{1,t} = MB_{1,t} \tag{3.22}$$

$$MBC^d_{i,t} = MB_{i,t} - MB_{i-1,t} \tag{3.23}$$

$$MB_{i,t} = \gamma_{0,t} + \sum_{j<i} \gamma_{j,t} MB_{j,t} + e_{i,t} \tag{3.24}$$

$$MBC^r_{i,t} = e_{i,t} \tag{3.25}$$

Figures 3.3 and 3.4 show market beliefs for the 1-month investment horizon. From Table 3.2 and Table 3.3, we see similar and consistent results for excess volatility. Panel (7) shows that the loadings on the first two market belief changes are significant at 5 percent level, while the last two are not. If the expected return is a martingale, the later market belief should be less volatile than the earlier market belief. I thus interpret the results as showing that investors can estimate future expected returns accurately at first in the short-term, but as time goes by, there is much more noise and investors cannot correctly forecast future expected returns. Another interesting finding is that the fourth market belief (three months earlier) has a negative and significant loading, which is a finding that may require further study. The evidence suggests that information from option markets are more effectively incorporated into investors' beliefs 5 and 6 months before. As time passes, there is more noise and beliefs become less accurate. There is also evidence of excess volatility.

3.3.3 Long-term Belief Evolution

In this subsection, I discuss the long-term (six-month horizon) market belief evolution. Denote the first and earliest market belief $MB^{3,4}_{t-4}$ as $MB_{1,t}$, followed by $MB^{2,3}_{t-3}$ as $MB_{2,t}$, $MB^{1,2}_{t-2}$ as $MB_{3,t}$, and $MB^{0,1}_{t-1}$ as $MB_{4,t}$. Figure 3.6 shows market beliefs for the 6-month investment horizon. I run the following regressions:

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MB_{i,t} + \epsilon_{i,t} \tag{3.26}$$

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MB_{1,t} + \beta_{2,t} MB_{2,t} + \beta_{3,t} MB_{3,t} + \beta_{4,t} MB_{4,t} + \epsilon_t \tag{3.27}$$

For the above equations, $i = 1, 2, 3, 4$. Table 3.4 reports the results. There are 5,157 observations from 1996 to 2017. The latest six-month market belief is a good estimate of the corresponding expected return, while the earlier market beliefs are noisy. The latest market belief for the 6-month investment horizon is significant at 1 percent level, in contrast with the case of 1-month investment horizon in the previous subsection.

Table 3.5 and Table 3.6 show how beliefs about expected returns on the market evolve over time. The regressions are:

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MBC^{x}_{i,t} + \epsilon_{i,t} \tag{3.28}$$

$$R_{m,t} - R_{f,t} = \beta_{0,t} + \beta_{1,t} MBC^{x}_{1,t} + \beta_{2,t} MBC^{x}_{2,t} + \beta_{3,t} MBC^{x}_{3,t} + \beta_{4,t} MBC^{x}_{4,t} + \epsilon_{t} \tag{3.29}$$

For the above equations, $i = 1, 2, 3, 4$ and $x = d, r$. $MBC^{d}_{i,t}$ and $MBC^{r}_{i,t}$ are unexpected changes in market beliefs based on the difference and regression methods, respectively. Specifically, for $i = 2, 3, 4$ and $x = d, r$, they are defined as follows:

$$MBC^{x}_{1,t} = MB_{1,t} \tag{3.30}$$

$$MBC^{d}_{i,t} = MB_{i,t} - MB_{i-1,t} \tag{3.31}$$

$$MB_{i,t} = \gamma_{0,t} + \sum_{j<i} \gamma_{j,t} MB_{j,t} + e_{i,t} \tag{3.32}$$

$$MBC^{r}_{i,t} = e_{i,t} \tag{3.33}$$

Figures 3.7 and 3.8 show market beliefs for the 6-month investment horizon. From Table 3.5 and Table 3.6 we see that the long-term beliefs are compatible with expected returns being a martingale. The 6-month investment horizon case produces different results from the 1-month horizon case. The latest belief change is loaded positively at the 1 percent significance level. For the earlier long-term belief estimates, they are not statistically significant. The results suggest that investors are more able to to estimate long-term (i.e. 6-month) expected returns than short-term (i.e. 1-month) expected returns at the latest interval. The short-term and long-term analyses yield opposite results. Understanding the mechanisms through which investors form and update their beliefs over short and long horizons is an interesting question for further study.

3.4 Out-of-sample Tests

In this section, I perform out-of-sample tests following Welch and Goyal (2007). If my predictors are good measures of market belief evolution, they should perform out-of-sample. The out-of-sample R^2 measure is defined as follows:

$$R^2_{OS} = 1 - \frac{\epsilon_t^2}{e_t^2} \tag{3.34}$$

where ϵ_t is the error term of the model where market beliefs are used to predict future realized returns on the market, while e_t is the error term when the historical average is used as a predictor. I use a rolling window of 3 years (about 750 trading days). As I have multiple predictors, I also conduct the combination forecast out-of-sample analysis proposed by Rapach et al. (2010).

For the 1-month investment horizon, I have 6 predictors from the past 6 months. The out-of-sample R-square is 5.5 percent and the adjusted out-of-sample R-square is 5.3 percent. The uncertainty measure I construct has an out-of-sample R-square of 0.1 percent, while the first two principal components also have an out-of-sample R-square of 0.1 percent. For the 6-month investment horizon, I have 4 predictors from the past 2 years. The out-of-sample R-square is 24.1 percent and the adjusted out-of-sample R-square is 23.9 percent. The uncertainty measure I construct has an out-of-sample R-square of 1.8 percent, while the first two principal components also have an out-of-sample R-square of 23.1 percent. The combination forecast out-of-sample analysis does not improve the out-of-sample R-square.

The findings show that my measures of market belief evolution and uncertainty not only capture a significant portion of the market risk premium, but also that they perform quite well out-of-sample.

3.5 Uncertainty Premium

A natural question is whether the variation in the evolution of market beliefs captures an uncertainty premium. In this section, I define a measure of uncertainty based on market belief changes. I then show that this measure captures an economically large and statistically significant uncertainty premium. I use the measure provided by Martin (2017) as the market risk premium.

A natural way to measure uncertainty is to take the standard deviation of the different measures of the same expected return over time. In particular, for the short-term belief changes (1-month investment horizon), I have six measures of the expected return over the same time interval, and I take the standard deviation of the six measures, that is:

$$UVIX_t = std(MB_{1,t}, MB_{2,t}, MB_{3,t}, MB_{4,t}, MB_{5,t}, MB_{6,t}) \tag{3.35}$$

For the long-term market belief changes (6-month investment horizon), the uncertainty measure can be defined analogously. In addition, I also conduct a principal component analysis to get the first two principal components capturing the variation of the market belief measures. Figure 3.5 and 3.9 show the comparison of different measures and market risk premium for the 1-month and 6-month investment horizons, respectively.

This procedure generates a time-series measure of uncertainty based on market belief changes. The measure is high frequency (on a daily basis). Using options data, I construct daily belief measures, thus the uncertainty measure is also on a daily frequency. This is a major advantage compared to other measures of uncertainty based on survey or macroeconomics data.

Table 3.7 reports the correlation matrix of the average market risk premium, current market risk premium by Martin (2017), my uncertainty measure, and the first two principal components of the market belief variable at different time points. As Table 3.7 shows, the measure of uncertainty has a large correlation (i.e. a correlation of 0.709 with average perceived risk premium) with market risk premium.

I confirm these findings using regression analysis. I regress the market risk premium on the uncertainty measure and several control variables. The control variables are the first two principal components, VIX, and the difference between VIX and my uncertainty measure. Tables 3.8, 3.9, and 3.10 report the results of the following regressions:

$$E(R_{m,t}) - R_{f,t} = \beta_{0,t} + \beta_{1,t} UVIX_t + \epsilon_{i,t} \tag{3.36}$$

$$E(R_{m,t}) - R_{f,t} = \beta_{0,t} + \beta_{1,t} PC_{i,t} + \epsilon_{i,t} \tag{3.37}$$

$$E(R_{m,t}) - R_{f,t} = \beta_{0,t} + \beta_{1,t}PC_{1,t} + \beta_{2,t}PC_{2,t} + \epsilon_{i,t} \tag{3.38}$$

$$E(R_{m,t}) - R_{f,t} = \beta_{0,t} + \beta_{1,t}UVIX_t + \beta_{2,t}PC_{1,t} + \beta_{3,t}PC_{2,t} + \epsilon_{i,t} \tag{3.39}$$

$$E(R_{m,t}) - R_{f,t} = \beta_{0,t} + \beta_{1,t}UVIX_{i,t} + controls + \epsilon_{i,t} \tag{3.40}$$

From Tables 3.8, 3.9, and 3.10, we see that the uncertainty measure captures a significant portion of the risk premium. Also, we see that it contains information different from that in VIX. While the principal components contain information about the variation in market beliefs, the uncertainty measure captures a significant premium even after controlling for the principal components. In Table 3.8, I use the latest perceived market risk premium, while in Table 3.9, I use the average perceived market risk premium from monthly beliefs in the past 6 months. The results show that the uncertainty measure enters significantly at the 1 percent level. Table 3.10 shows that the uncertainty measure is different from VIX. After controlling for VIX and the difference between VIX and the uncertainty measure, the uncertainty measure still captures some of the market risk premium. My measure of uncertainty is not simply a measure of stock market volatility but the uncertainty coming from the evolution of market beliefs. Tables 3.11, 3.12, 3.13, 3.14 repeat the process for the long-term market belief evolution (6-month investment horizon) and find similar results.

3.6 Individual Stocks

Martin and Wagner (2018) follow the approach of Martin (2017) to construct a measure of the expected return on a stock. In this section, I redo my analysis for the stocks in the market index. The definition of market beliefs is analogous to the previous section. Other than the formula for the expected return, there are two main differences for implementing the same procedure to individual stocks. First, for each day, I need to figure out the stocks in the S&P 500 index. For this, I rely on the index constituents data from Compustat. The dataset specifies the period in which each stock is in the index, so that I can get a set of stocks in the index on a daily basis. Second, I need to control for risk factors; I include MKT, SMB, HML, and MOM.

The results show significant noise in the belief updating process for individual stocks. There is no clear excess volatility pattern. The volatility is large and quite variable. This is somewhat expected, as individual stock returns are supposed to be noisier and harder to predict than the market returns. The results suggest a high level of uncertainty in the belief evolution process for individual stocks. I also construct an uncertainty measure, $UVIX$, for individual stocks. Not surprisingly, the measure captures an uncertainty premium.

3.7 Conclusion

I propose a novel way to measure the evolution of market beliefs about expected returns. I use this measure to estimate market beliefs about expected returns on the market and on individual stocks from 1996 to 2017. My idea is to use the information reflected in option prices to elicit information about how market beliefs evolve. I document several facts and run multiple empirical tests to substantiate the robustness of my results. In the short-term analysis (1-month investment horizon), investors can forecast the expected return for a future fixed time interval more accurately at first. At the same time, there is more noise as time passes. This shows a pattern of excess volatility. In the long-term analysis (6-month investment horizon), the pattern is reversed; there is no excess volatility.

Moreover, I construct a new measure of uncertainty based on the evolution of market beliefs. I show that my measure captures an economically large and statistically significant premium. Out-of-sample tests further strengthen my results. Finally, I apply the same procedure to the expected return on the stock. I also uncover an uncertainty premium for the individual stocks.

My paper makes three key contributions. First, I provide a novel way to track the evolution of market beliefs for a (future) fixed time interval. While Martin (2017) and Martin and Wagner (2018)'s measure captures the expected return from time 0 to T, I construct a novel measure that captures the expected return from time T to T+1. Meanwhile, from time 0 to T-1, my measure gives T-1 estimates for the same time interval T to T+1. Market belief updates can be measured in a model- and survey-free manner. Second, I document excess volatility, which goes against the theory that the expected return is a martingale. Investors can forecast the expected return over a future fixed time interval more accurately at first, while there is more noise as time goes by.

This excess volatility finding contributes to the literature on excess volatility of stock prices and cashflows, providing another aspect to investigate for further research. For example, information from excess volatility in expected returns can be extracted to find additional return and risk factor predictors. Finally, I construct a robust new measure of uncertainty, $UVIX$, based on the uncertainty embedded in the evolution of market beliefs, which is different from existing measures of stock market volatility such as VIX. The uncertainty comes from the volatility of investors' beliefs over the same time interval at other time points. The second moment of the market belief measure contains different information from VIX, as is shown in the empirical tests. To the best of my knowledge, I am the first to empirically measure market belief evolution and quantify the uncertainty embedded in the learning process of market participants. My work provides empirical evidence that can speak to the theoretical mechanism of how market beliefs evolve and why there is excess volatility in short-term belief paths. My methodology and measures can also contribute to further studies on individual stocks and the evolution of market beliefs during the FOMC cycle.

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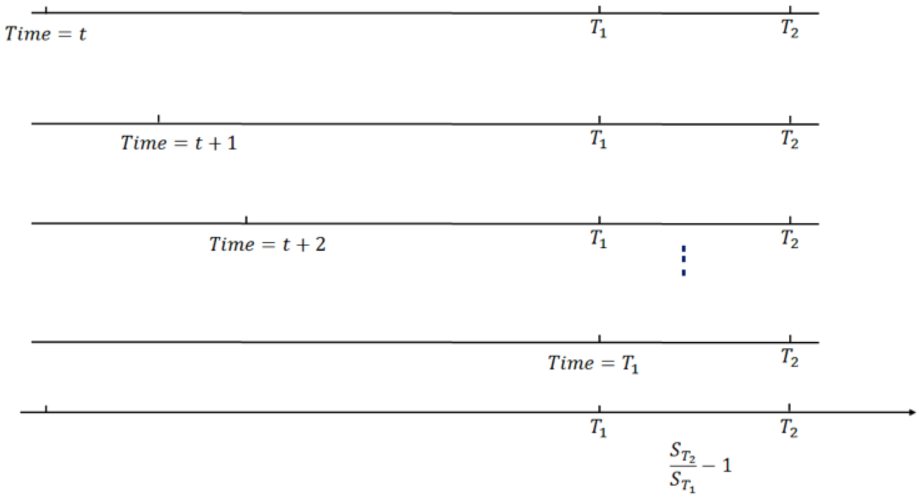


Figure 3.1: Illustration of Measure Construction

Notes: This figure illustrates how market belief measure is constructed.

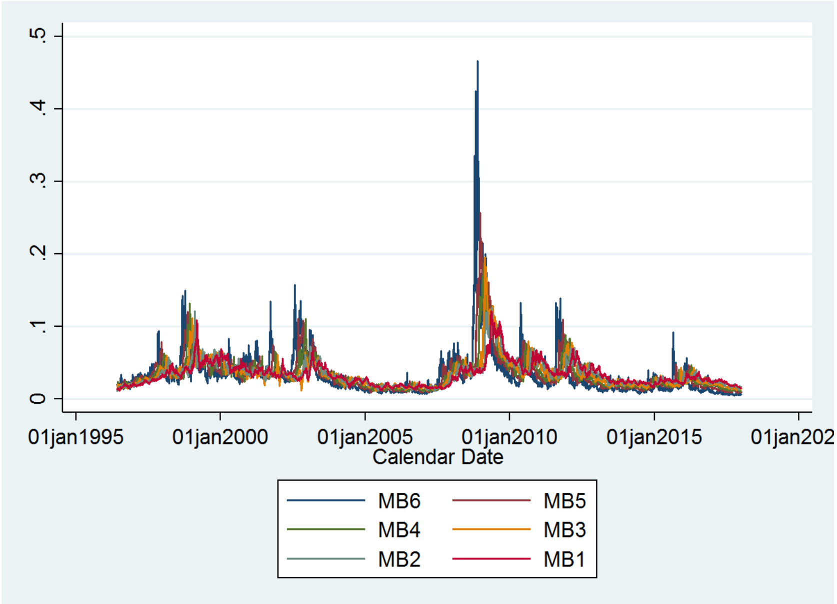


Figure 3.2: Market Belief (1-month investment horizon)

Notes: This figure shows the market belief in expected return of the 1-month investment horizon. $MB1$ denotes the first and earliest market belief of investors in the past 6 months, followed by $MB2$, $MB3$, $MB4$, $MB5$, and $MB6$.

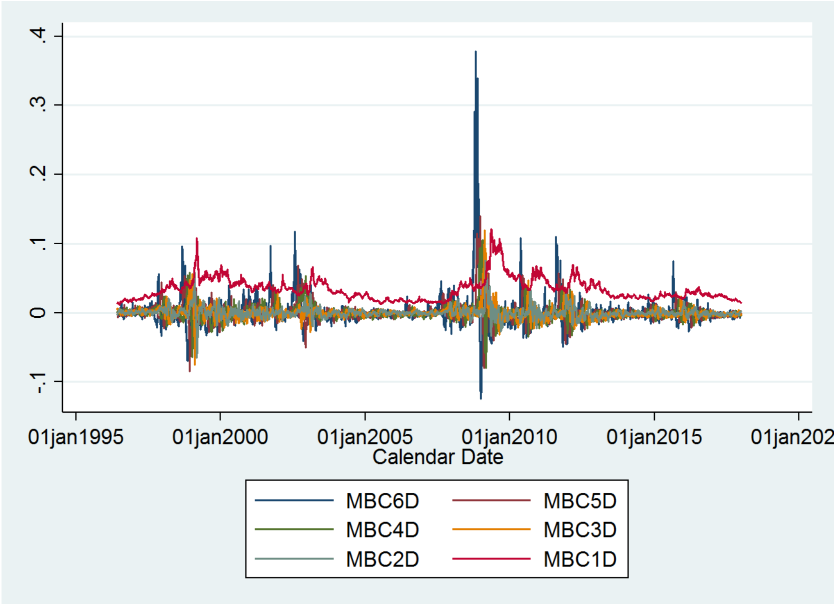


Figure 3.3: Market Belief Change by Difference Method (1-month investment horizon)

Notes: This figure shows the change of market belief in expected return of the 1-month investment horizon by difference method.

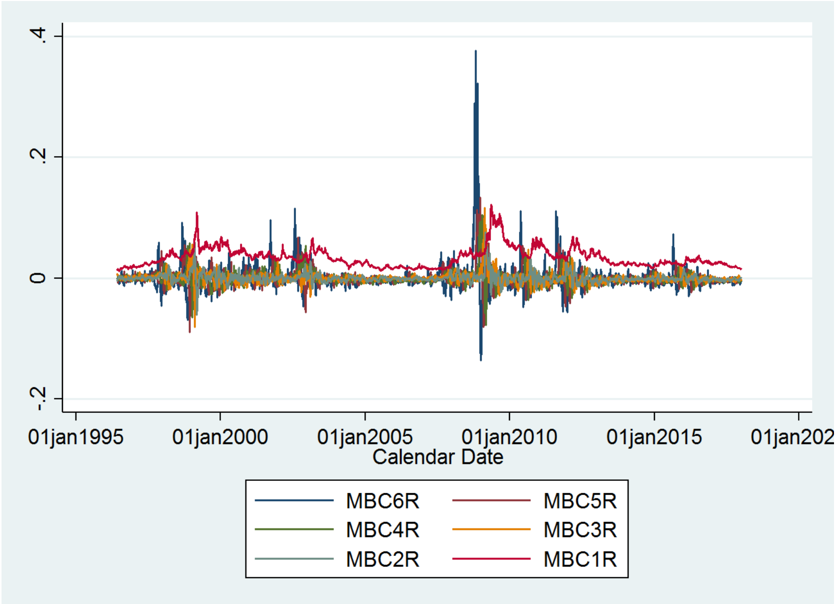


Figure 3.4: Market Belief Change by Regression Method (1-month investment horizon)

Notes: This figure shows the change of market belief in expected return of the 1-month investment horizon by regression method.

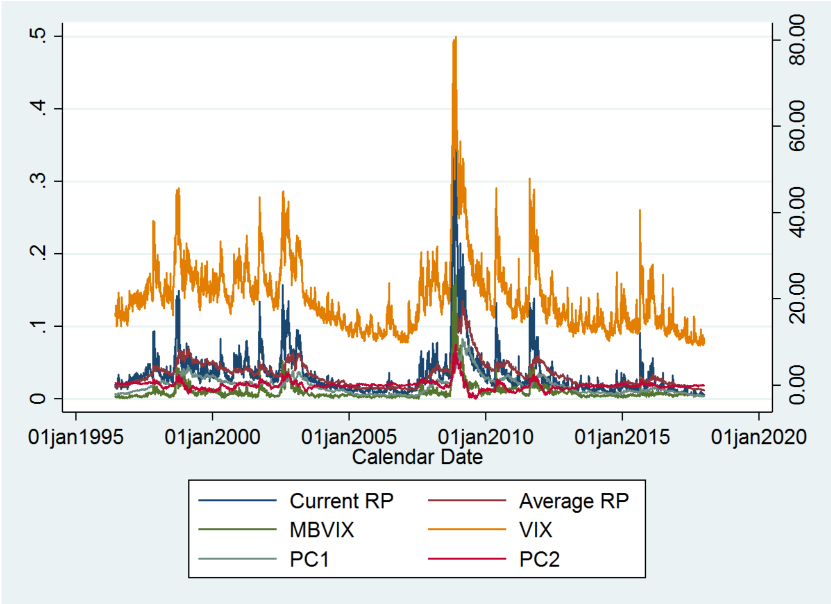


Figure 3.5: Comparison of Different Measures and Market Risk Premium (1-month investment horizon)

Notes: This figure compares different measures of the 1-month investment and market risk premium.

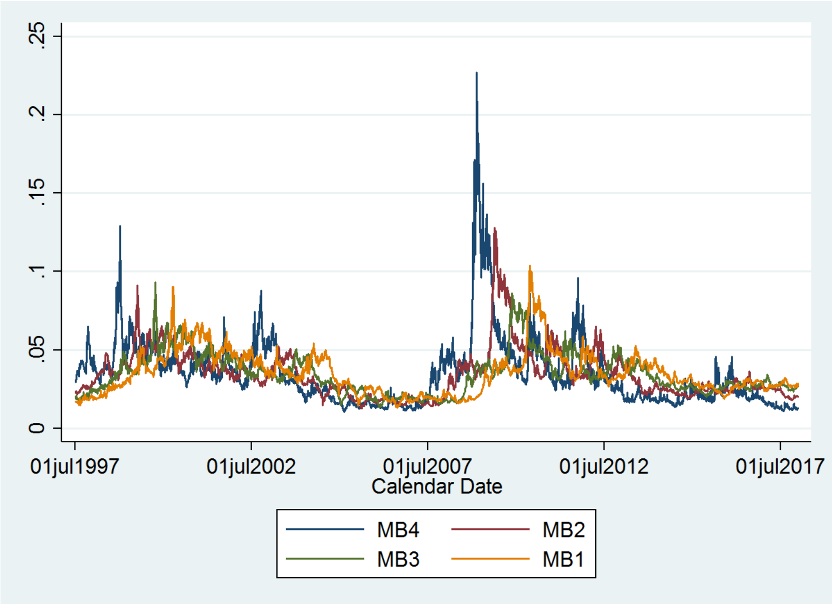


Figure 3.6: Market Belief (6-month investment horizon)

Notes: This figure shows the market belief in expected return of the 6-month investment horizon. $MB1$ denotes the first and earliest market belief of investors in the past 2 years, followed by $MB2$, $MB3$, and $MB4$.

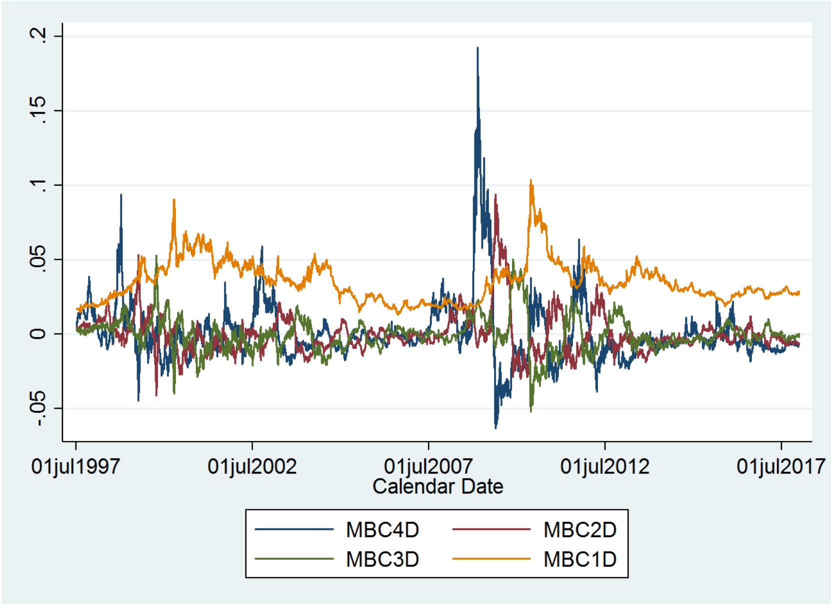


Figure 3.7: Market Belief Change by Difference Method (6-month investment horizon)

Notes: This figure shows the change of market belief in expected return of the 6-month investment horizon by difference method.

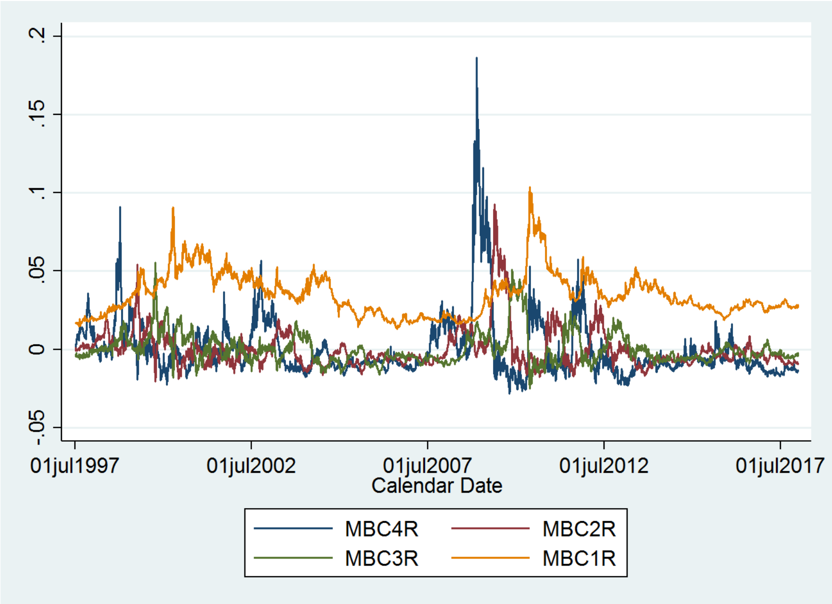


Figure 3.8: Market Belief Change by Regression Method (6-month investment horizon)

Notes: This figure shows the change of market belief in expected return of the 6-month investment horizon by regression method.

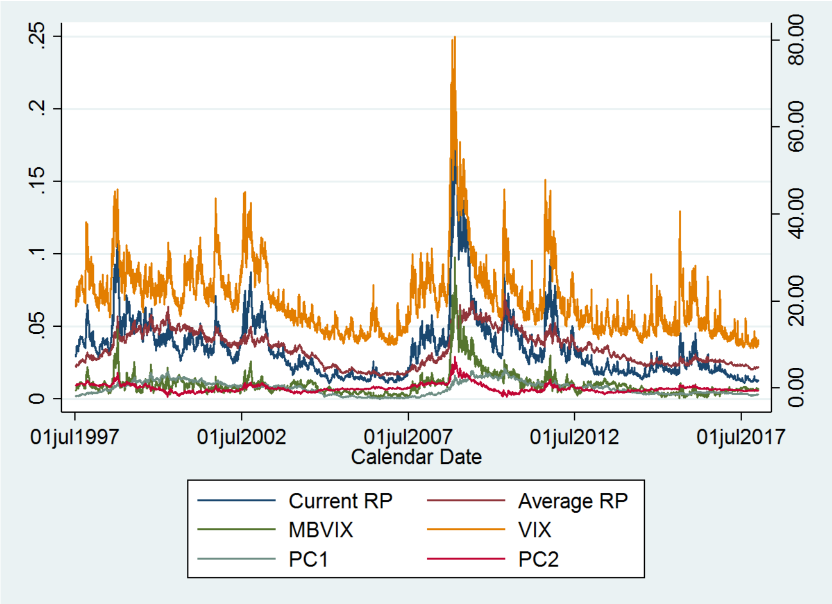


Figure 3.9: Comparison of Different Measures and Market Risk Premium (6-month investment horizon)

Notes: This figure compares different measures of the 6-month investment and market risk premium.

Table 3.1: Short-term Evolvement Analysis of Realized Return on Market Belief Estimates (1996-2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MB_{1,t}$	2.386*						-3.825
	(1.239)						(3.191)
$MB_{2,t}$		3.450**					5.828
		(1.454)					(3.959)
$MB_{3,t}$			2.700				5.762
			(1.770)				(3.628)
$MB_{4,t}$				0.705			-7.894**
				(1.672)			(3.579)
$MB_{5,t}$					1.131		2.636
					(1.252)		(2.623)
$MB_{6,t}$						0.837	0.199
						(1.047)	(1.496)
constant	-0.00268	-0.0393	-0.0134	0.0541	0.0394	0.0494	-0.0149
	(0.0425)	(0.0490)	(0.0574)	(0.0531)	(0.0403)	(0.0326)	(0.0424)
N	5432	5432	5432	5432	5432	5432	5432

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.18) and (3.19), which shows the coefficients and significance level of regression analysis of realized return on market belief estimates of short-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief 6 months ago, (2) market belief 5 months ago, (3) market belief 4 months ago, (4) market belief 3 months ago, (5) market belief 2 months ago, (6) market belief 1 month ago, (7) all the market belief estimates. There are 5432 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.2: Short-term Evolvement Analysis of Realized Return on Market Belief Change by Difference Method (1996-2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MBC^d_{1,t}$	2.386*						2.708**
	(1.239)						(1.272)
$MBC^d_{2,t}$		6.401					6.532**
		(3.946)					(3.250)
$MBC^d_{3,t}$			0.475				0.704
			(4.304)				(3.383)
$MBC^d_{4,t}$				-5.206**			-5.058**
				(2.591)			(2.496)
$MBC^d_{5,t}$					2.132		2.836
					(2.138)		(1.966)
$MBC^d_{6,t}$						0.463	0.199
						(1.497)	(1.496)
constant	-0.00268	0.0769***	0.0781***	0.0785***	0.0776***	0.0780***	-0.0149
	(0.0425)	(0.0225)	(0.0229)	(0.0225)	(0.0226)	(0.0227)	(0.0424)
N	5432	5432	5432	5432	5432	5432	5432

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.20) and (3.21), which shows the coefficients and significance level of regression analysis of realized return on market belief change by difference method of short-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief change 6 months ago, (2) market belief change 5 months ago, (3) market belief change 4 months ago, (4) market belief change 3 months ago, (5) market belief change 2 months ago, (6) market belief change 1 month ago, (7) all the market belief change. There are 5432 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.3: Short-term Evolvement Analysis of Realized Return on Market Belief Change by Regression Method (1996-2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MBC^r_{1,t}$	2.386*						2.386**
	(1.239)						(1.203)
$MBC^r_{2,t}$		7.126*					7.126**
		(3.940)					(3.419)
$MBC^r_{3,t}$			0.145				0.145
			(4.191)				(3.470)
$MBC^r_{4,t}$				-4.696*			-4.696*
				(2.559)			(2.420)
$MBC^r_{5,t}$					2.881		2.881
					(2.144)		(1.951)
$MBC^r_{6,t}$						0.199	0.199
						(1.496)	(1.496)
constant	-0.00268	0.0780***	0.0780***	0.0780***	0.0780***	0.0780***	-0.00268
	(0.0425)	(0.0225)	(0.0227)	(0.0226)	(0.0226)	(0.0227)	(0.0423)
N	5432	5432	5432	5432	5432	5432	5432

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.20) and (3.21), which shows the coefficients and significance level of regression analysis of realized return on market belief change by regression method of short-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief change 6 months ago, (2) market belief change 5 months ago, (3) market belief change 4 months ago, (4) market belief change 3 months ago, (5) market belief change 2 months ago, (6) market belief change 1 month ago, (7) all the market belief change. There are 5432 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.4: Long-term Evolvement Analysis of Realized Return on Market Belief Estimates (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$MB_{1,t}$	-0.0260				-0.0585
	(0.870)				(1.028)
$MB_{2,t}$		0.354			-0.639
		(0.760)			(1.025)
$MB_{3,t}$			0.752		-0.207
			(0.577)		(0.937)
$MB_{4,t}$				1.924***	2.109***
				(0.540)	(0.636)
constant	0.0670**	0.0538*	0.0401**	-0.00113	0.0237
	(0.0334)	(0.0283)	(0.0194)	(0.0181)	(0.0310)
N	5157	5157	5157	5157	5157

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.26) and (3.27), which shows the coefficients and significance level of regression analysis of realized return on market belief estimates of long-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief 4 months ago, (2) market belief 3 months ago, (3) market belief 2 months ago, (4) market belief change 1 months ago, (5) all the market belief change. There are 5157 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.5: Long-term Evolvement Analysis of Realized Return on Market Belief Change by Difference Method (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$MBC^d_{1,t}$	-0.0260				1.204
	(0.870)				(0.845)
$MBC^d_{2,t}$		0.517			1.262
		(0.881)			(0.896)
$MBC^d_{3,t}$			0.695		1.901**
			(0.898)		(0.958)
$MBC^d_{4,t}$				1.748***	2.109***
				(0.601)	(0.636)
constant	0.0670**	0.0663***	0.0660***	0.0654***	0.0237
	(0.0334)	(0.0104)	(0.0103)	(0.0102)	(0.0310)
N	5157	5157	5157	5157	5157

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.28) and (3.29), which shows the coefficients and significance level of regression analysis of realized return on market belief change by difference method of long-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief 4 months ago, (2) market belief 3 months ago, (3) market belief 2 months ago, (4) market belief change 1 months ago, (5) all the market belief change. There are 5157 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.6: Long-term Evolvement Analysis of Realized Return on Market Belief Change by Regression Method (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$MBC^r_{1,t}$	-0.0260				-0.0260
	(0.870)				(0.858)
$MBC^r_{2,t}$		0.652			0.652
		(0.869)			(0.829)
$MBC^r_{3,t}$			0.905		0.905
			(0.882)		(0.894)
$MBC^r_{4,t}$				2.109***	2.109***
				(0.634)	(0.636)
constant	0.0670**	0.0661***	0.0661***	0.0661***	0.0670**
	(0.0334)	(0.0103)	(0.0103)	(0.0102)	(0.0334)
N	5157	5157	5157	5157	5157

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.28) and (3.29), which shows the coefficients and significance level of regression analysis of realized return on market belief change by regression method of long-term market belief evolvement. Column (1) estimates the loading of market realized return on market belief 4 months ago, (2) market belief 3 months ago, (3) market belief 2 months ago, (4) market belief change 1 months ago, (5) all the market belief change. There are 5157 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.7: Correlation Matrix of Market Risk Premium and Uncertainty Measures of Short-term Market Belief Evolvement (1996-2017)

	(1)				
	$AverageRP$	$CurrentRP$	$UVIX$	PC_1	PC_2
$AverageRP$	1				
$CurrentRP$	0.763***	1			
$UVIX$	0.709***	0.899***	1		
PC_1	0.985***	0.647***	0.606***	1	
PC_2	0.165***	0.658***	0.606***	0	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports the correlation matrix of average market risk premium, current market risk premium, my uncertainty measure, and first two principal components of short-term market belief evolvement from 1996 to 2017.

Table 3.8: Regression Analysis of Current Market Risk Premium on Uncertainty Measures of Short-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$UVIX$	2.640***				1.196***
	(0.0810)				(0.198)
PC_1		0.0108***		0.0108***	0.00666***
		(0.000974)		(0.000502)	(0.000682)
PC_2			0.0227***	0.0227***	0.0142***
			(0.00312)	(0.00214)	(0.00123)
constant	0.00882***	0.0342***	0.0342***	0.0342***	0.0227***
	(0.000789)	(0.00112)	(0.00114)	(0.000549)	(0.00179)
N	5432	5432	5432	5432	5432

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.36), (3.37), (3.38), and (3.39), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and principal components of short-term market belief evolvement. Column (1) estimates current market risk premium on my uncertainty measure, (2) current market risk premium on first principal component, (3) current market risk premium on second principal component, (4) current market risk premium on first two principal components, (5) current market risk premium on my uncertainty measure and first two principal components. There are 5432 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.9: Regression Analysis of Average Market Risk Premium on Uncertainty Measures of Short-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$UVIX$	1.127***				0.0765***
	(0.135)				(0.0115)
PC_1		0.00886***		0.00886***	0.00860***
		(0.000129)		(0.0000328)	(0.0000411)
PC_2			0.00308*	0.00308***	0.00254***
			(0.00169)	(0.000133)	(0.0000735)
constant	0.0232***	0.0340***	0.0340***	0.0340***	0.0333***
	(0.00119)	(0.000139)	(0.000825)	(0.0000351)	(0.000104)
N	5432	5432	5432	5432	5432

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to equation (3.36), (3.37), (3.38), and (3.39), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and principal components of short-term market belief evolvement. Column (1) estimates average market risk premium on my uncertainty measure, (2) average market risk premium on first principal component, (3) average market risk premium on second principal component, (4) average market risk premium on first two principal components, (5) average market risk premium on my uncertainty measure and first two principal components. There are 5432 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.10: Regression Analysis of Market Risk Premium on Uncertainty Measures and VIX of Short-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)	(6)
$UVIX$	1.127***	0.231*		2.640***	1.098***	
	(0.135)	(0.127)		(0.0810)	(0.146)	
VIX		0.00157***	0.232*		0.00271***	1.100***
		(0.000117)	(0.127)		(0.0000914)	(0.146)
$VIX - UVIX$			0.231*			1.098***
			(0.127)			(0.146)
constant	0.0232***	-0.000284	-0.000284	0.00881***	-0.0315***	-0.0315***
	(0.00119)	(0.00166)	(0.00166)	(0.000789)	(0.000945)	(0.000945)
N	5430	5430	5430	5430	5430	5430

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.36) and (3.40), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and VIX of short-term market belief evolvement. Column (1) estimates average market risk premium on my uncertainty measure, (2) average market risk premium on my uncertainty measure and VIX, (3) average market risk premium on my uncertainty measure, VIX, and the difference between my uncertainty measure and VIX, (4) current market risk premium on my uncertainty measure, (5) current market risk premium on my uncertainty measure and VIX, (6) current market risk premium on my uncertainty measure, VIX, and the difference between my uncertainty measure and VIX. There are 5430 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.11: Correlation Matrix of Market Risk Premium and Uncertainty Measures of Long-term Market Belief Evolvement (1996-2017)

	(1)				
	mp_avg	m1sp	std	f1	f2
$AverageRP$	1				
$CurrentRP$	0.731***	1			
$UVIX$	0.672***	0.858***	1		
PC_1	0.975***	0.563***	0.536***	1	
PC_2	0.209***	0.760***	0.642***	2.79e-08	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports the correlation matrix of average market risk premium, current market risk premium, $UVIX$, and first two principal components of long-term market belief evolvement from 1996 to 2017.

Table 3.12: Regression Analysis of Current Market Risk Premium on Uncertainty Measures of Long-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$UVIX$	2.254***				0.594***
	(0.0552)				(0.0698)
PC_1		0.00829***		0.00829***	0.00651***
		(0.000575)		(0.000325)	(0.000293)
PC_2			0.0179***	0.0179***	0.0145***
			(0.00119)	(0.000691)	(0.000486)
constant	0.0123***	0.0349***	0.0349***	0.0349***	0.0290***
	(0.000677)	(0.000843)	(0.000667)	(0.000330)	(0.000681)
N	5157	5157	5157	5157	5157

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.36), (3.37), (3.38), and (3.39), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and principal components of long-term market belief evolvement. Column (1) estimates current market risk premium on my uncertainty measure, (2) current market risk premium on first principal component, (3) current market risk premium on second principal component, (4) current market risk premium on first two principal components, (5) current market risk premium on my uncertainty measure and first two principal components. There are 5157 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.13: Regression Analysis of Average Market Risk Premium on Uncertainty Measures of Long-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)
$UVIX$	0.950***				0.0720***
	(0.0845)				(0.00877)
PC_1		0.00772***		0.00772***	0.00751***
		(0.0000862)		(0.0000429)	(0.0000380)
PC_2			0.00265***	0.00265***	0.00224***
			(0.000681)	(0.0000745)	(0.0000730)
constant	0.0252***	0.0347***	0.0347***	0.0347***	0.0340***
	(0.000860)	(0.000123)	(0.000542)	(0.0000433)	(0.0000852)
N	5157	5157	5157	5157	5157

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.36), (3.37), (3.38), and (3.39), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and principal components of long-term market belief evolvement. Column (1) estimates average market risk premium on my uncertainty measure, (2) average market risk premium on first principal component, (3) average market risk premium on second principal component, (4) average market risk premium on first two principal components, (5) average market risk premium on my uncertainty measure and first two principal components. There are 5157 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Table 3.14: Regression Analysis of Market Risk Premium on Uncertainty Measures and VIX of Long-term Market Belief Evolvement (1996-2017)

	(1)	(2)	(3)	(4)	(5)	(6)
$UVIX$	0.950***	0.494***		2.254***	0.841***	
	(0.0846)	(0.0952)		(0.0552)	(0.0629)	
VIX		0.000600***	0.494***		0.00186***	0.843***
		(0.0000657)	(0.0952)		(0.0000538)	(0.0629)
$VIX - UVIX$			0.494***			0.841***
			(0.0952)			(0.0629)
constant	0.0252***	0.0175***	0.0175***	0.0123***	-0.0116***	-0.0116***
	(0.000860)	(0.00121)	(0.00121)	(0.000677)	(0.000863)	(0.000863)
N	5156	5156	5156	5156	5156	5156

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the regression results according to (3.36) and (3.40), which shows the coefficients and significance level of regression analysis of market risk premium on $UVIX$ and VIX of long-term market belief evolvement. Column (1) estimates average market risk premium on my uncertainty measure, (2) average market risk premium on my uncertainty measure and VIX, (3) average market risk premium on my uncertainty measure, VIX, and the difference between my uncertainty measure and VIX, (4) current market risk premium on my uncertainty measure, (5) current market risk premium on my uncertainty measure and VIX, (6) current market risk premium on my uncertainty measure, VIX, and the difference between my uncertainty measure and VIX. There are 5156 observations on daily basis from 1996 to 2017. Newey and West (1987) robust standard errors are reported in parentheses below coefficient estimates.

Appendix A

Appendix to The Dual Role of Cryptocurrency Exchanges

A.1 For Online Publication: Theory Appendix

Proposition 1: At any equilibrium, the opportunistic cryptocurrency exchange's strategy consists in lying with positive probability for any q and lying for sure for q close to 1.

Proof: $x(q) = 0$ is not an equilibrium strategy ($q^S = q^F = q^N = q$), contradiction to $L(q) > 0$ when $x(q) = 0$. Observe a failure is on the equilibrium path of an honest exchange. No realization allows to detect any deviation from $x(q) = 0$.

$$\lim_{q \to 1} V(q^S) = \lim_{q \to 1} V(q^F) = \lim_{q \to 1} V(q^N) = V(1)$$

$$\Rightarrow \lim_{q \to 1} [L(q) + \delta(V(q^F) - V(q^N))] = L(1) > 0$$

$$\Rightarrow \lim_{q \to 1} x(q) = 1$$

Proposition 2: If $T_0 > \frac{\gamma L(\bar{q})}{1-\delta}$, there exists a unique equilibrium that opportunistic cryptocurrency exchange always tells the truth: $x^*(\bar{q}) = 0$. If $\bar{q}$ is large enough, exchanges with large trading revenue will seldom choose to cheat. In extreme case when $\bar{q}$ is 1, exchanges with large trading revenue will never cheat.

Proof: Consider the case that the cryptocurrency exchange has reputation $\bar{q}$. In the truthful equilibrium, the reputation does not matter. The value function is a constant equal to $\frac{T_0+\gamma L(\bar{q})}{1-\delta}$. The reputation also remains constant, and trading revenue T_0 will not be affected. Hence, $x^*(\bar{q}) = 0$ is an equilibrium strategy for the opportunistic cryptocurrency exchange. If the exchange deviate to cheat and list a bad project, then its reputation will drop, because when $x(q) > 0$

$$q^F = \frac{q}{1 + (1-q)\frac{(1-\gamma)x(q)}{\gamma p}} < q$$

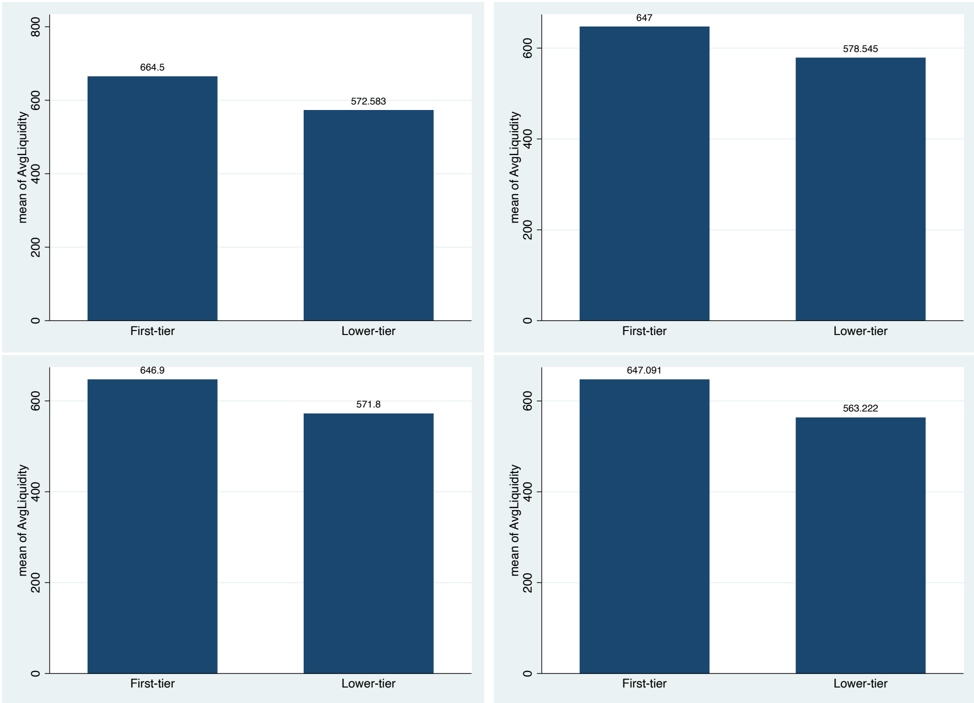
By deviating from the no-cheating equilibrium, the opportunistic cryptocurrency exchange will receive no more than $\frac{\gamma L(\bar{q})}{1-\delta}$, but lose T_0. Thus, the incentive constraint is

$$T_0 > \frac{\gamma L(\bar{q})}{1-\delta}$$

Now consider the opportunistic cryptocurrency exchanges with reputation $q > \bar{q}$. They may choose to cheat, but are disciplined by the threshold $\bar{q}$. The larger $\bar{q}$ increases the probability of $Prob(q^F < \bar{q})$, when they will lose trading revenue forever. In the extreme case that $\bar{q} = 1$, there will be no cheating, as any failure result will lead to the permanent lose of trading revenue.

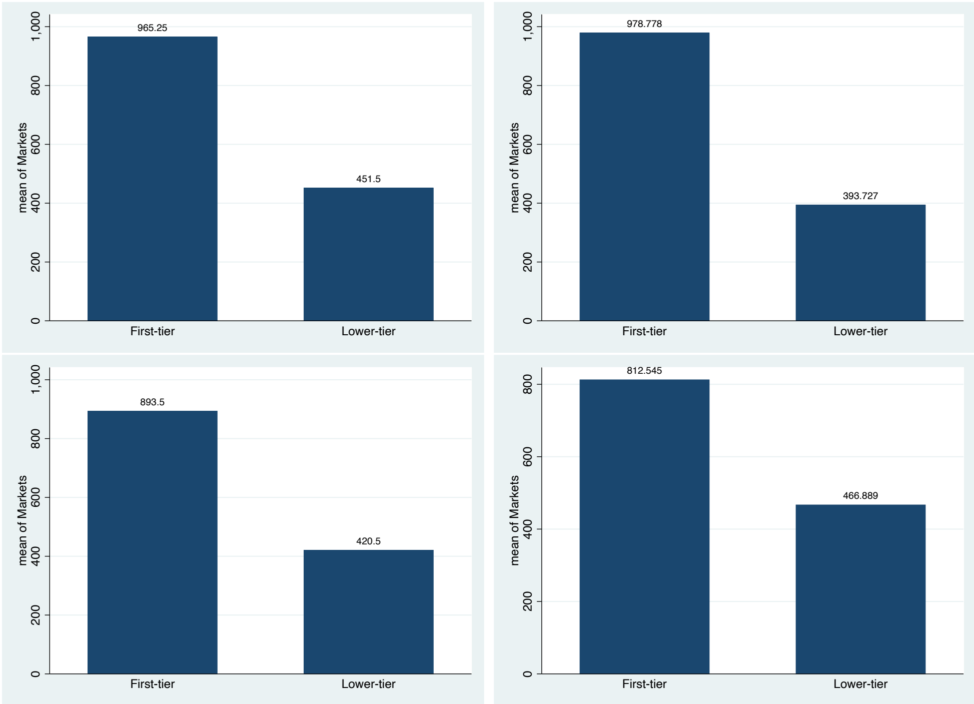
A.2 Appendix: Additional Figures

Figure A.1: Average Liquidity: First-tier v.s. Lower-tier Exchanges



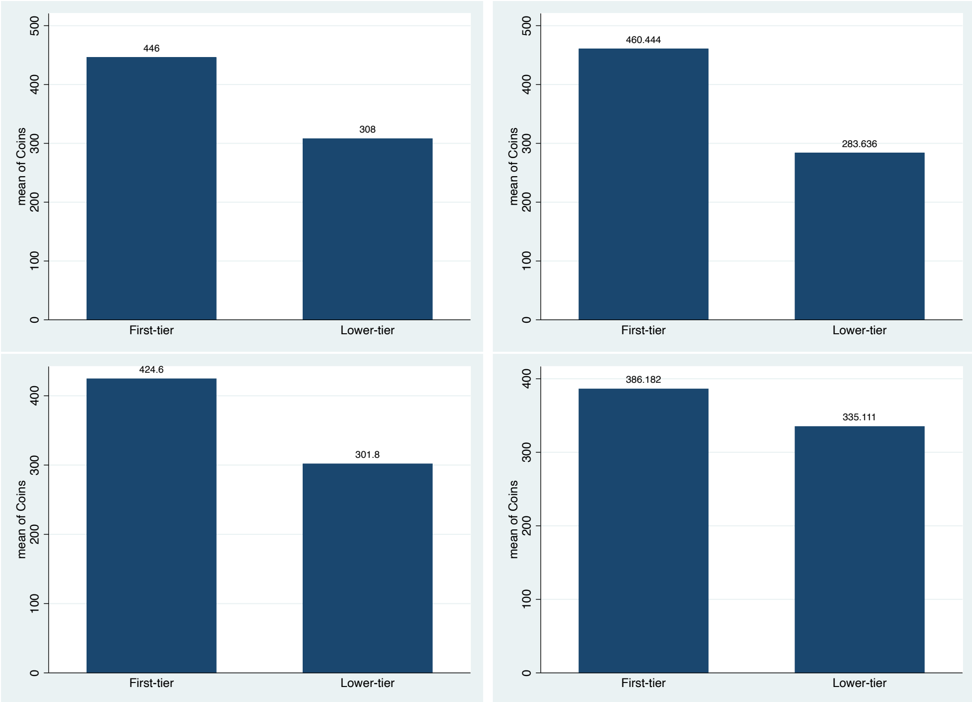
Notes: This figure plots the average liquidity of first-tier exchanges and lower-tier exchanges in 2017, 2018, 2019, and 2020. First-tier exchanges are defined as the top 10 exchanges based on web traffic measure. Lower-tier exchanges in this figure are the 10 exchanges ranking from 11 to 20 based on web traffic measure. Average liquidity data for each cryptocurrency exchange is from Coinmarketcap as of 15 July 2022.

Figure A.2: Number of Markets: First-tier v.s. Lower-tier Exchanges



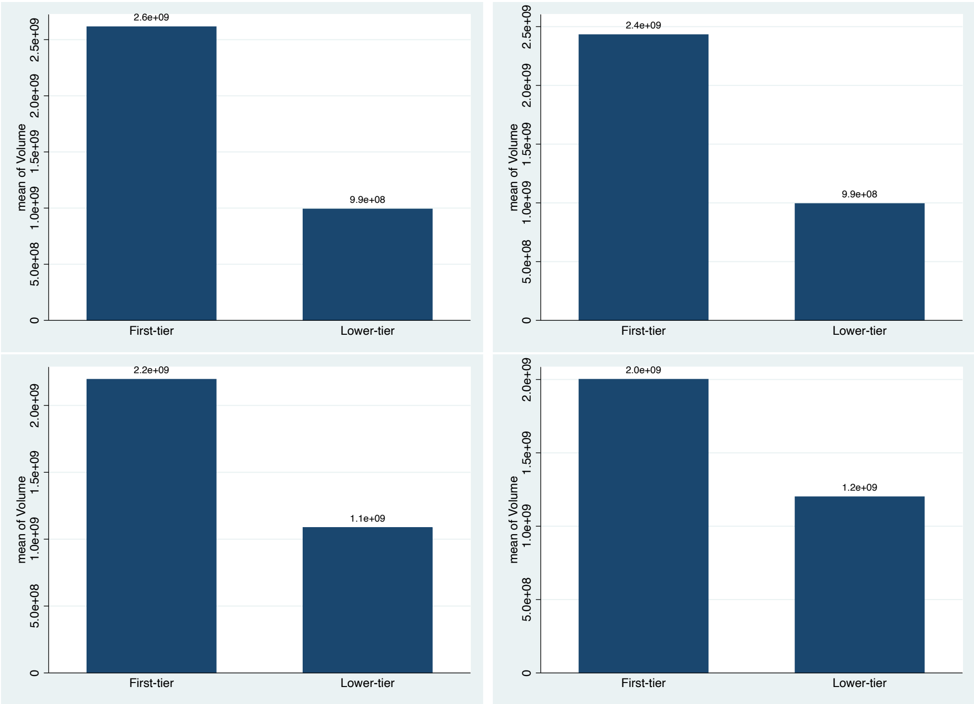
Notes: This figure plots the average number of markets of first-tier exchanges and lower-tier exchanges in 2017, 2018, 2019, and 2020. First-tier exchanges are defined as the top 10 exchanges based on web traffic measure. Lower-tier exchanges in this figure are the 10 exchanges ranking from 11 to 20 based on web traffic measure. Number of markets data for each cryptocurrency exchange is from Coinmarketcap as of 15 July 2022.

Figure A.3: Number of Coins: First-tier v.s. Lower-tier Exchanges



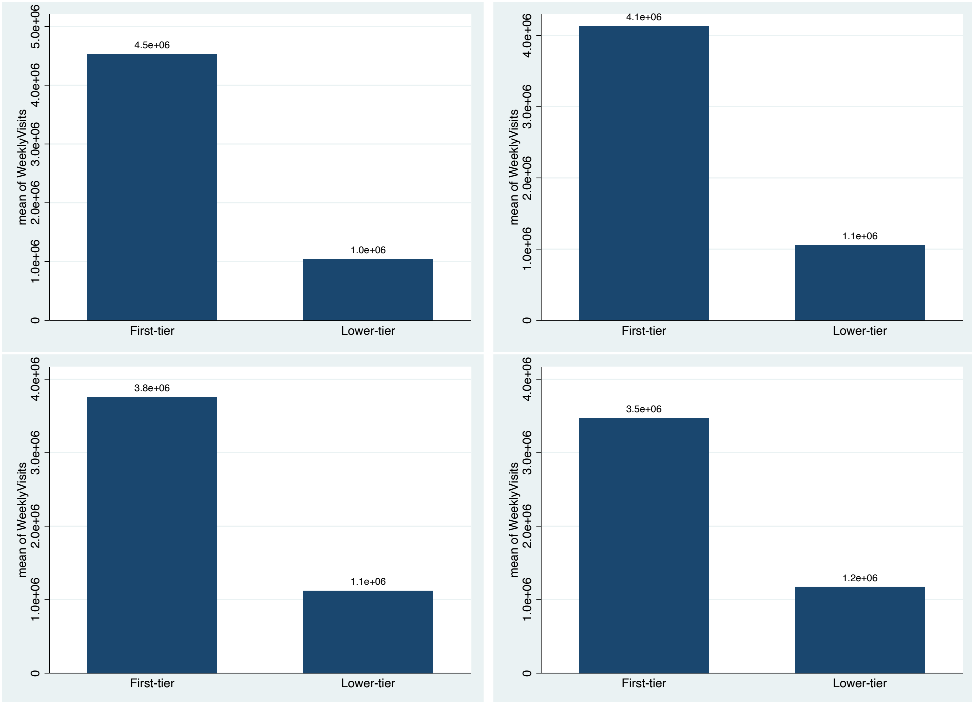
Notes: This figure plots the average number of coins of first-tier exchanges and lower-tier exchanges in 2017, 2018, 2019, and 2020. First-tier exchanges are defined as the top 10 exchanges based on web traffic measure. Lower-tier exchanges in this figure are the 10 exchanges ranking from 11 to 20 based on web traffic measure. Number of coins data for each cryptocurrency exchange is from Coinmarketcap as of 15 July 2022.

Figure A.4: Trading Volume: First-tier v.s. Lower-tier Exchanges



Notes: This figure plots the average trading volume of first-tier exchanges and lower-tier exchanges in 2017, 2018, 2019, and 2020. First-tier exchanges are defined as the top 10 exchanges based on web traffic measure. Lower-tier exchanges in this figure are the 10 exchanges ranking from 11 to 20 based on web traffic measure. Trading volume (24h) data for each cryptocurrency exchange is from Coinmarketcap as of 15 July 2022.

Figure A.5: Weekly Visits: First-tier v.s. Lower-tier Exchanges



Notes: This figure plots the average weekly visits of first-tier exchanges and lower-tier exchanges in 2017, 2018, 2019, and 2020. First-tier exchanges are defined as the top 10 exchanges based on web traffic measure. Lower-tier exchanges in this figure are the 10 exchanges ranking from 11 to 20 based on web traffic measure. Weekly visits data for each cryptocurrency exchange is from Coinmarketcap as of 15 July 2022.

A.3 Robustness Checks: Empirical Analysis

Table A.1: Token Performance Across Exchanges: Web Traffic Measure (Robustness Check)

	Ret1	Ret3	Ret7	Ret14	Ret21	Ret30
$First$	-0.0146	0.0532	0.0488	0.0837	0.0298***	0.0576***
	(-0.47)	(0.77)	(0.98)	(1.44)	(2.63)	(2.71)
# observations	664	664	664	664	662	662

	Ret60	Ret90	Ret180	Ret360	Ret720	
$First$	0.0436***	0.0413***	0.0772***	0.0536***	0.0688***	
	(2.99)	(3.78)	(4.56)	(4.98)	(5.76)	
# observations	659	652	635	593	434	

	AdjRet1	AdjRet3	AdjRet7	AdjRet14	AdjRet21	AdjRet30
$First$	-0.0298	0.0564	0.0790	0.0718	0.0588**	0.0631***
	(-0.78)	(0.91)	(1.32)	(1.59)	(2.52)	(2.90)
# observations	664	664	664	664	662	662

	AdjRet60	AdjRet90	AdjRet180	AdjRet360	AdjRet720	
$First$	0.0484***	0.0572***	0.0798***	0.0672***	0.0733***	
	(3.17)	(3.88)	(4.62)	(5.78)	(6.02)	
# observations	659	652	635	593	434	

Notes: This table reports the difference of token performance across the two types of exchanges (i.e. first-tier exchange and second-tier exchanges) based on web traffic measure. Specifically, this table compares the performance of tokens that are listed by first-tier and second-tier exchanges 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Ret_i = \alpha + \beta First_i + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_i$$

where $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, and Ret_i stands for short-term log return and long-term log return.

$$AdjRet_i = \alpha + \beta First_i + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_i$$

where $AdjRet_i = Ret_i - Ret_{BTC}$.
The first two rows report the results of raw performance, while the last two rows report the results of the adjusted performance, i.e. raw performance subtracted by the corresponding performance of Bitcoin.

Table A.2: Token Performance Across Exchanges: Exchange Token (Robustness Check)

	Ret1	Ret3	Ret7	Ret14	Ret21	Ret30
$\text{Ret}_{ex,t-30\to t-1}$	0.0318*	0.0275**	0.0311**	0.0294*	0.0389***	0.0750**
	(1.82)	(2.28)	(2.17)	(1.91)	(2.98)	(2.22)
# observations	236	236	236	236	234	234
	Ret60	Ret90	Ret180	Ret360	Ret720	
$\text{Ret}_{ex,t-30\to t-1}$	0.178***	0.110***	0.093	0.0345	0.0189	
	(3.98)	(2.67)	(1.45)	(1.01)	(0.78)	
# observations	233	230	226	217	141	
	AdjRet1	AdjRet3	AdjRet7	AdjRet14	AdjRet21	AdjRet30
$\text{Ret}_{ex,t-30\to t-1}$	0.0318***	0.0232***	0.0374*	0.0421***	0.0620*	0.0268
	(3.94)	(3.21)	(1.92)	(2.61)	(1.90)	(0.97)
# observations	236	236	236	236	234	234
	AdjRet60	AdjRet90	AdjRet180	AdjRet360	AdjRet720	
$\text{Ret}_{ex,t-30\to t-1}$	0.198***	0.182***	0.133	0.0684	0.0315	
	(4.37)	(2.88)	(1.09)	(1.45)	(1.32)	
# observations	233	230	226	217	141	

Notes: This table reports the effects of past exchange token return on the return of token listed on the exchange based on exchange token measure. Specifically, this table uses the past 1-month cryptocurrency exchange token return as a predictor to predict the listed token return 1,3,7,14,21, 30, 60, 90, 180, 360, and 720 days after its initial listing.

$$Ret_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_i$$

where $Ret_{exchange,t-30\to t-1}$ is past 1-month cryptocurrency exchange token return, Ret_i stands for the short-term and long-term log return of the token listed on the exchange, and $\gamma_{exchange}$ is the exchange fixed effects.

$$AdjRet_i = \alpha + \beta Ret_{exchange,t-30\to t-1} + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_i$$

where $AdjRet_i = Ret_i - Ret_{BTC}$.
The first two rows report the results of raw return, while the last two rows report the results of the adjusted return, i.e. raw return subtracted by the corresponding return of Bitcoin.

Table A.3: Token Performance and Exchange Token Characteristics (Robustness Check)

	(1) *Ret*	(2) *Ret*	(3) *Ret*	(4) *AdjRet*	(5) *AdjRet*	(6) *AdjRet*
$Ret_{exchange}$	0.0671***			0.0289***		
	(4.32)			(3.96)		
$\Delta MarketCap$		0.000835***			0.000678***	
		(10.88)			(6.79)	
$\Delta Volume$			0.000233***			0.000352***
			(7.02)			(6.49)
# observations	293132	210965	245779	293132	210965	245779

Notes: This table reports the effects of past exchange token performance on the return of token listed on the exchange using real-time daily return. Exchange tokens' characteristics are used as proxies, including past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change.

$$Ret_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return of the listed token, $X_{i,t-14\to t-1}$ stands for past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change, and γ_i is the token fixed effects.

$$AdjRet_{i,t} = \alpha + \beta X_{i,t-14\to t-1} + \gamma_{exchange} + \theta_{ListDate} + \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + +\epsilon_{i,t}$$

where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ stands for the daily return of Bitcoin. Column (1)-(3) shows the results of token return, while Column (4)-(6) exhibits the results of adjusted token return.

Table A.4: Token Performance and Exchange Token Characteristics: Heterogeneity (Robustness Check)

	(1) *Ret*	(2) *Ret*	(3) *Ret*	(4) *AdjRet*	(5) *AdjRet*	(6) *AdjRet*
$Ret_{exchange} \times First$	0.041**			0.129***		
	(2.01)			(5.82)		
$Ret_{exchange}$	0.0511***			0.0348**		
	(2.92)			(1.99)		
$\Delta MarketCap \times First$		0.000622***			0.000518***	
		(4.22)			(5.18)	
$\Delta MarketCap$		0.000412***			0.0000602	
		(4.17)			(0.88)	
$\Delta Volume \times First$			0.000396***			0.000689***
			(8.78)			(12.33)
$\Delta Volume$			0.0000358			-0.0000201
			(1.38)			(-0.69)
$First$	0.00577***	0.00348***	0.00834***	0.00621***	0.00268***	0.00537***
	(6.98)	(6.11)	(5.89)	(6.71)	(7.82)	(8.11)
# observations	293132	210965	245779	293132	210965	245779

Notes: This table reports the heterogeneous effects of past exchange token performance on the return of token listed on the exchange using real-time daily return. Exchange tokens' characteristics are used as proxies, including past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change.

$$Ret_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \gamma_{exchange} + \theta_{ListDate}$$
$$+ \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_{i,t}$$

where $Ret_{i,t}$ is the daily return of the listed token, $First_i$ is the dummy of whether the coin is listed by a first-tier exchange, $X_{i,t-14\to t-1}$ stands for past two-week average token return, past two-week average token market capitalization change, and past two-week average token trading volume change, and γ_i is the token fixed effects.

$$AdjRet_{i,t} = \alpha + \beta_1 X_{i,t-14\to t-1} \times First_i + \beta_2 X_{i,t-14\to t-1} + \beta_3 First_i + \gamma_{exchange} + \theta_{ListDate}$$
$$+ \kappa_{RaisedUSD} + \delta_{InitialSalePrice} + \epsilon_{i,t}$$

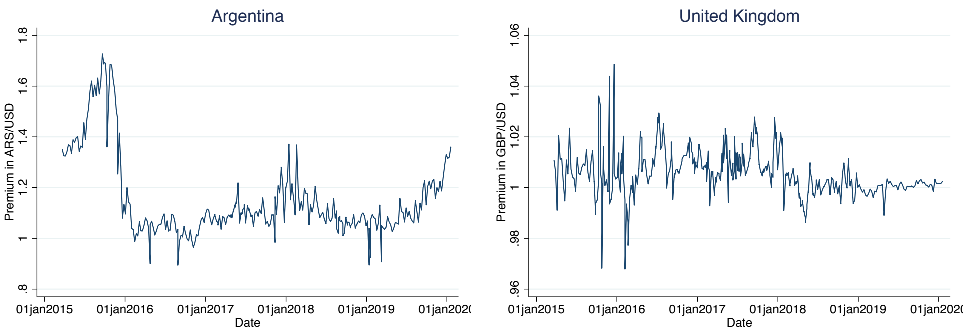
where $Adj\_Ret_{i,t} = Ret_{i,t} - Ret_{BTC,t}$, and $Ret_{BTC,t}$ stands for the daily return of Bitcoin. Column (1)-(3) shows the results of token return, while Column (4)-(6) exhibits the results of adjusted token return.

Appendix B

Appendix to Distrust and Cryptocurrency

B.1 Internet Appendix: Figures and Tables

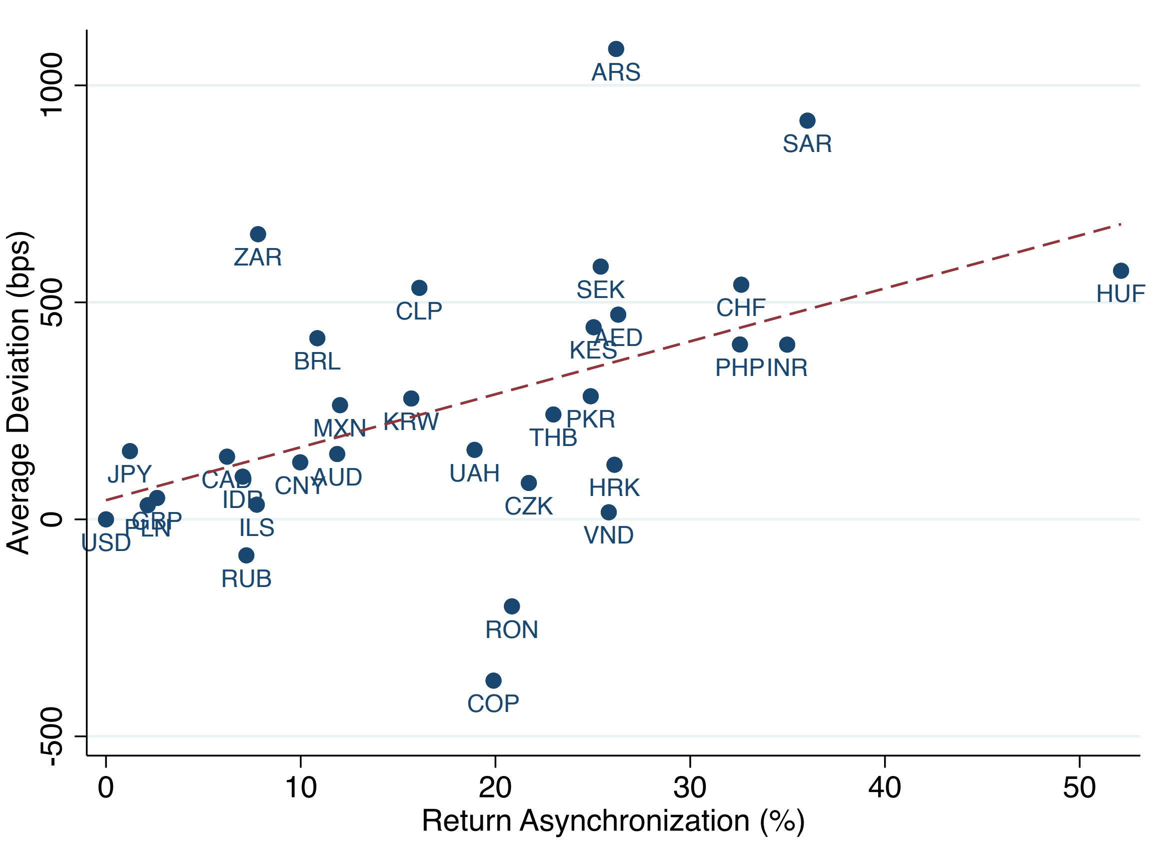
Figure B.1: Price Deviation - Argentina and United Kingdom



Notes: This figure plots the price deviations in Argentina and the United Kingdom. Price deviation in country c is defined as:

$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}}$$

Figure B.2: Return Asynchronization and Average Deviation

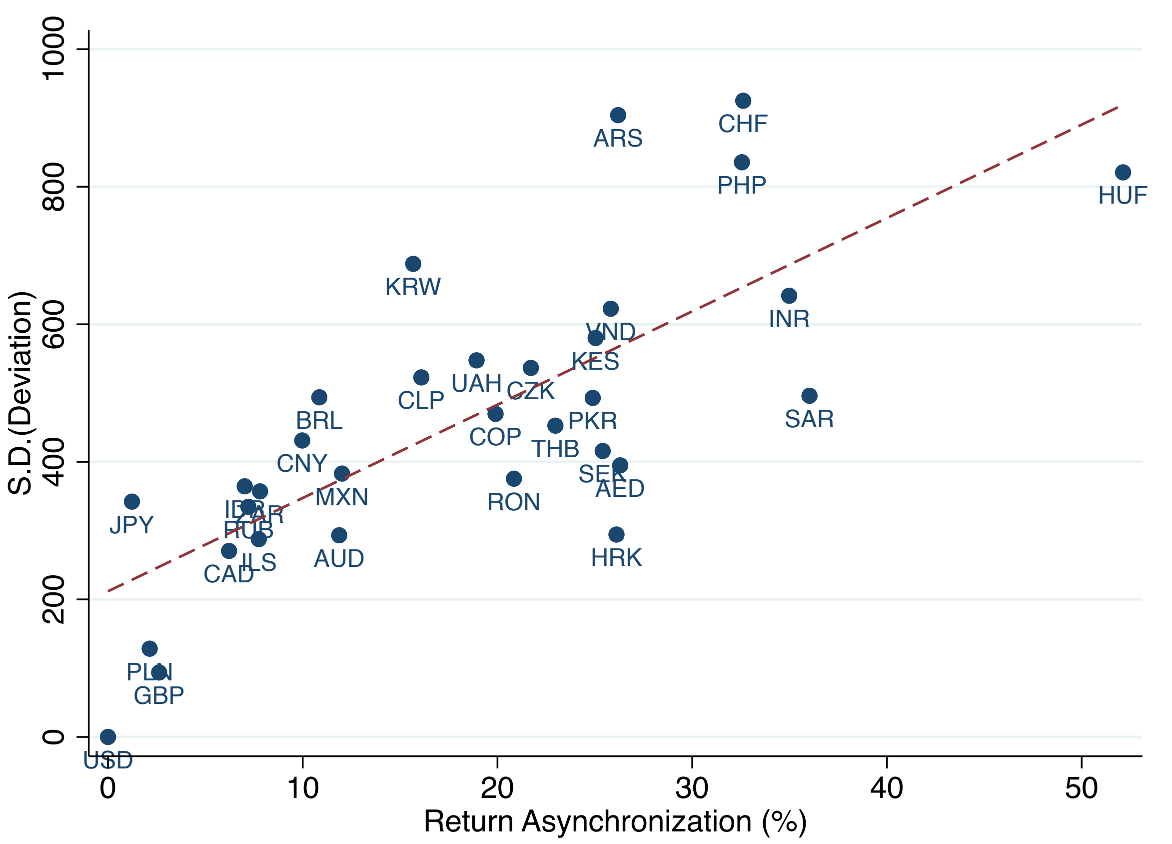


Notes: This figure shows the relationship between the average return asynchronization and the average price deviation by currency.

$$\overline{Deviation_c} = \beta \overline{Asyn_c} + \epsilon_c$$

where $\overline{Deviation_c}$ is the average price deviation, and $\overline{Asyn_c}$ is the average return asynchronization in country c.

Figure B.3: Return Asynchronization and SD(Deviation)

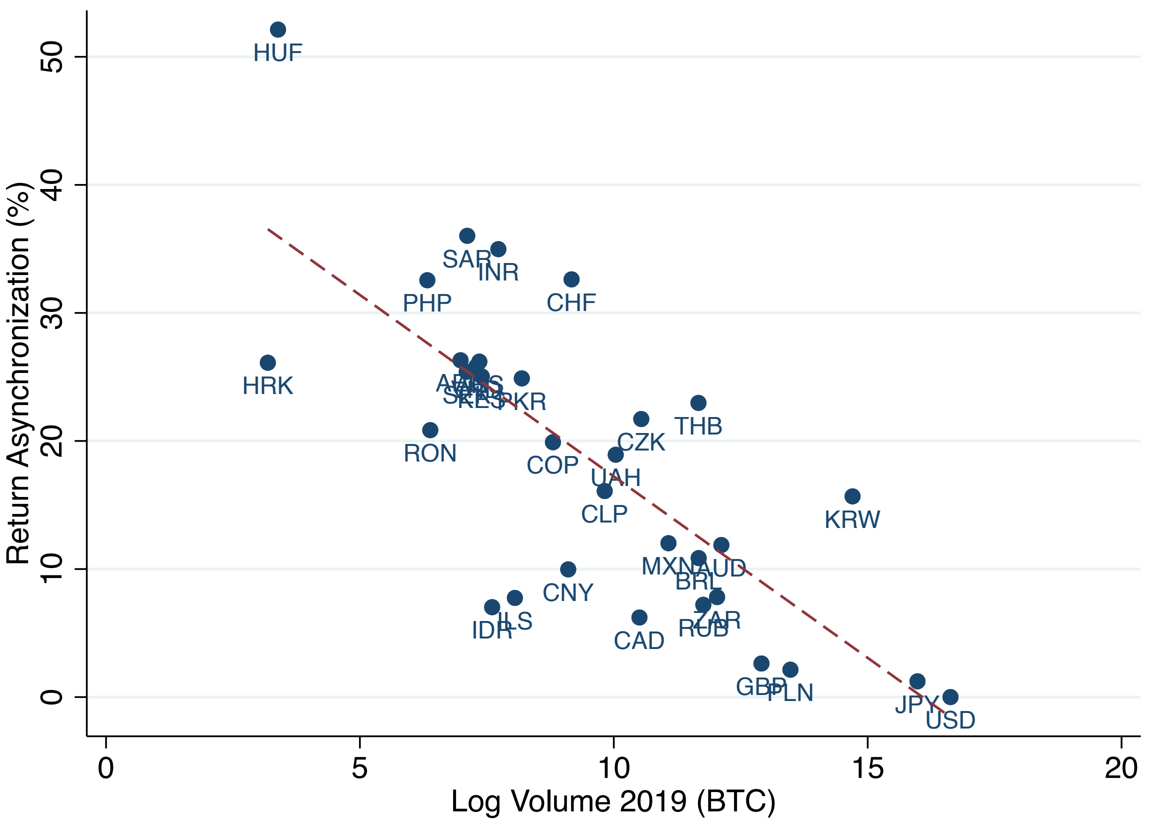


Notes: This figure shows the positive relationship between the average return asynchronization and the standard deviation of price deviations by currency.

$$SD(Deviation_c) = \beta\overline{Asyn_c} + \epsilon_c$$

where $SD(Deviation_c)$ is the standard deviation of price deviation, and $\overline{Asyn_c}$ is the average return asynchronization in country c.

Figure B.4: Return Asynchronization and Liquidity

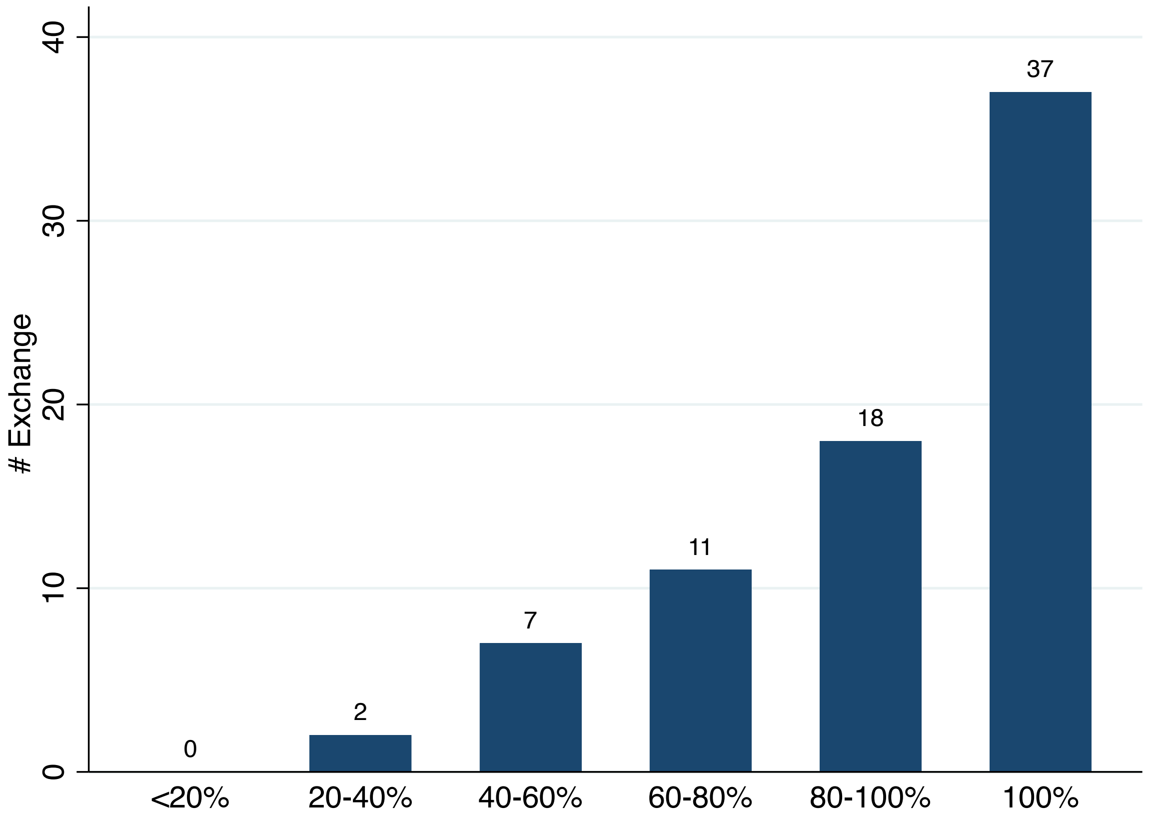


Notes: This figure plots the average return asynchronization and log trading volume in 2019.

$$\overline{Asyn_c} = \beta Log\_Vol_c + \epsilon_c$$

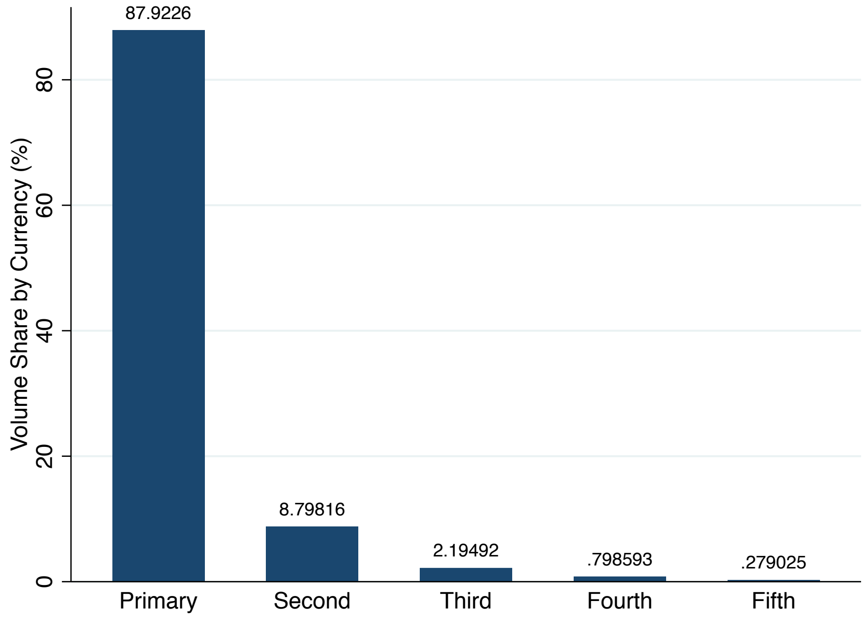
where $\overline{Asyn_c}$ is the average return asynchronization of country c, and Log_Vol_c is the log number of Bitcoins traded in 2019.

Figure B.5: Exchanges by Volume Share of Primary Trading Pair



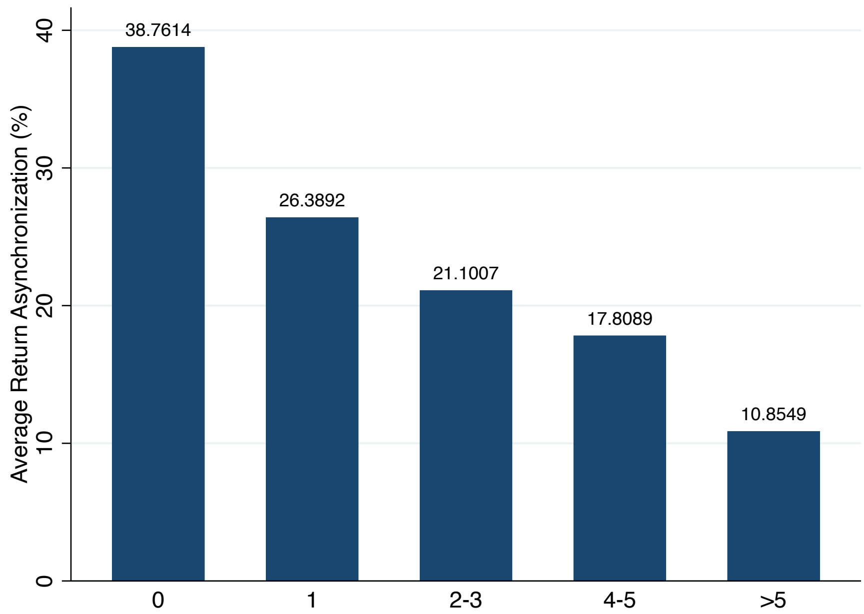
Notes: This figure plots the number of exchanges sorted into six categories by the primary trading pair's volume share. 37 out of 75 exchanges have only one fiat currency actively traded. The two "20-40%" exchanges are peer-to-peer listing platform (trading happens outside the exchange): Localbitcoins and Bisq.

Figure B.6: Average Volume Share in Top 5 Trading Pairs



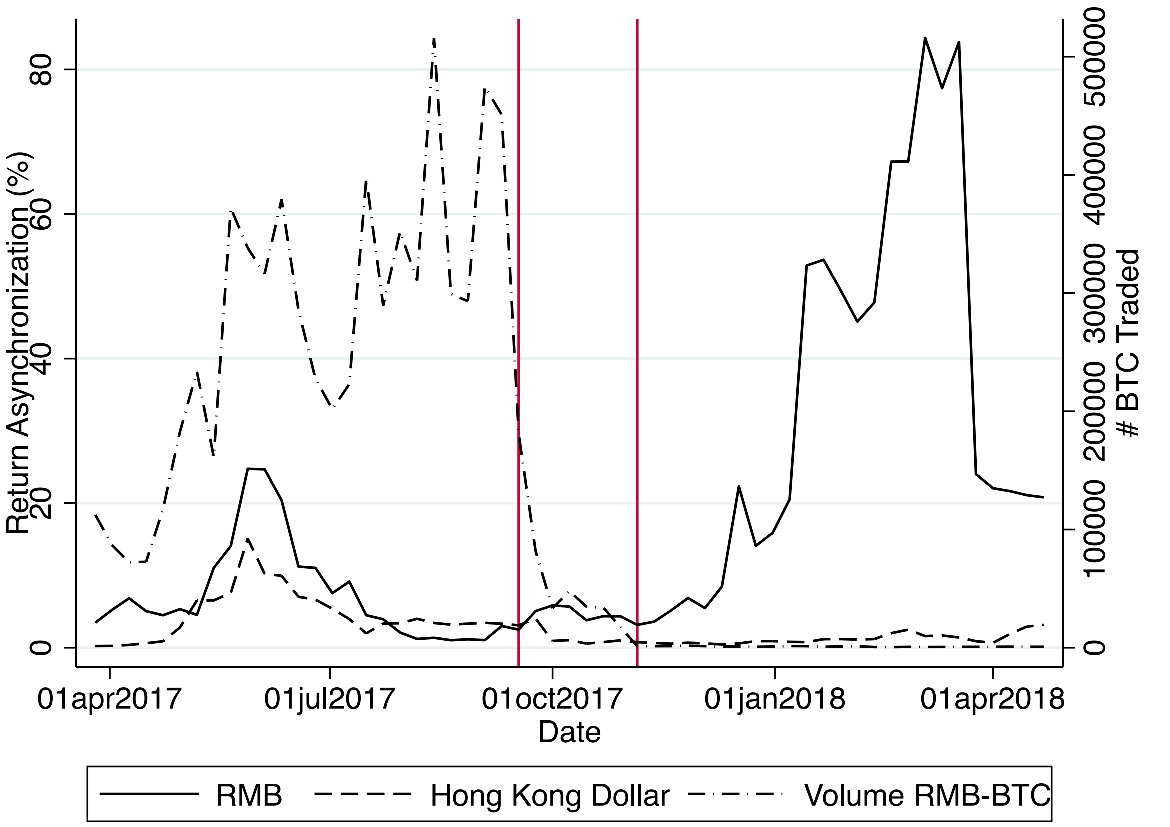
Notes: This figure plots the average volume share of the top 5 most active traded fiat currencies (with Bitcoin). The primary trading pair accounts for 87.9% of the total trading volume. The number sharply decreases to 8.80% for the second, 2.19% for the third, 0.80% for the fourth, and the 0.28% for the fifth active fiat currency.

Figure B.7: Average Return Asynchronization and Number of Top Exchanges by Currency



Notes: This figure plots the average return asynchronization against the number of exchanges with fiat trading pair by currency. For the 8 currencies with no top 100 exchanges covering their fiat currency, the average return asynchronization is 38.76%. The number decreases to 26.39% for the 7 currencies with 1 exchange, 21.10% for the 6 currencies with 2 to 3 exchanges, 17.80% for the 5 currencies with 4 to 5 exchanges, and 10.85% for the 6 currencies with more than 5 exchanges.

Figure B.8: China Ban - Friction

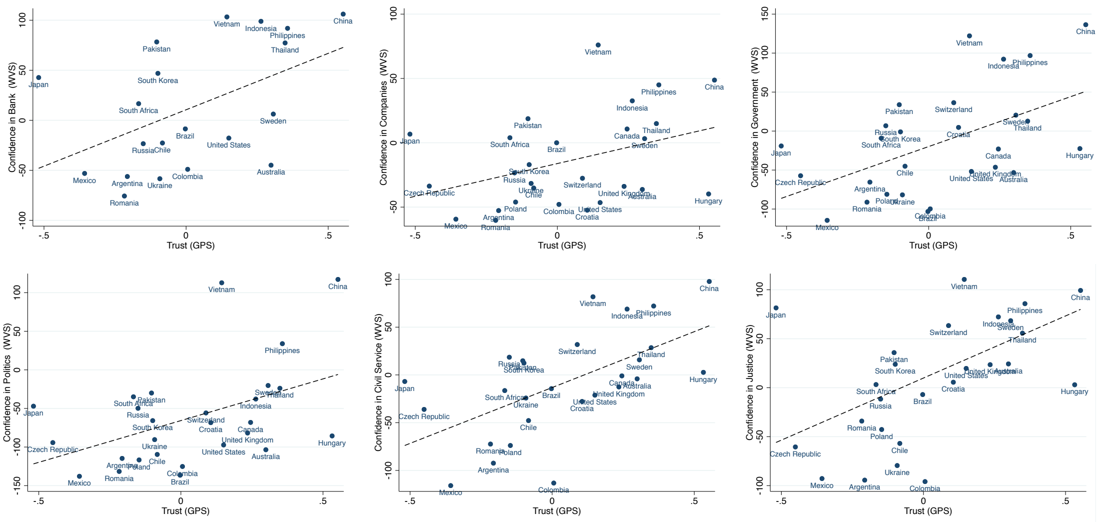


Notes: In September 2017, China started its plan to shut down cryptocurrency exchanges in the country. All cryptocurrency exchanges in Beijing and Shanghai were ordered to submit plans for winding down their operations by September 20^{th}, 2017. Leading crypto-exchanges started to stop trading at the end of the month, followed by Huobi and OKCoin. Chinese authorities decided to ban digital currencies as part of a plan for reducing the country's financial risks. The weekly trading volume (dash-dotted line) of Bitcoin drops from 450885.96 (10 Sep 2017) to 33387.74 (1 Oct 2017), to 1373.24 (5 Nov 2017). The solid line is the return asynchronization between Chinese RMB Bitcoin returns and US dollar returns. The dashed line is the return asynchronization between Hong Kong dollar Bitcoin returns and US dollar returns.

Figure B.9: Return Asynchronization and Law

Notes: This figure shows the relationship between return asynchronization and law across countries. There are five law status categories: “No regulation,” “Ban,” “Tax Law Only,” “Anti-Money Laundering Law Only,” and “Both Applied.”

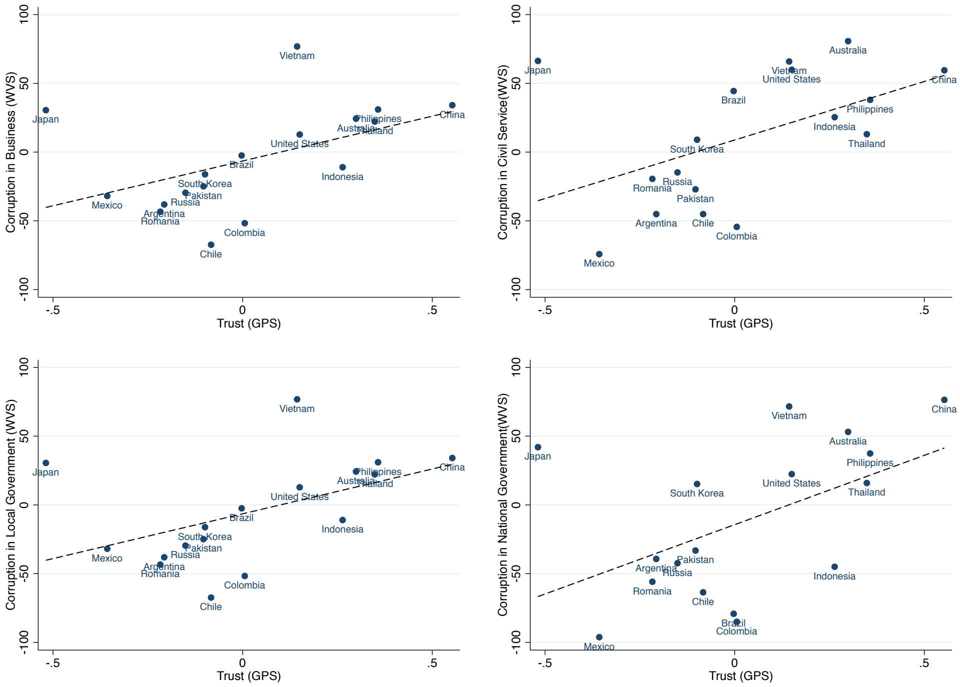
Figure B.10: Trust and Confidence in Institutions



Notes: This figure reports the relationship between trust and confidence scores in institutions, including banks, companies, government, politics, civil service, and justice. The trust measure is from the Global Preference Survey, and the confidence scores are calculated from the Global Value Survey.

$$Confidence_c^{WVS} = Trust_c^{GPS} + \gamma\epsilon_c$$

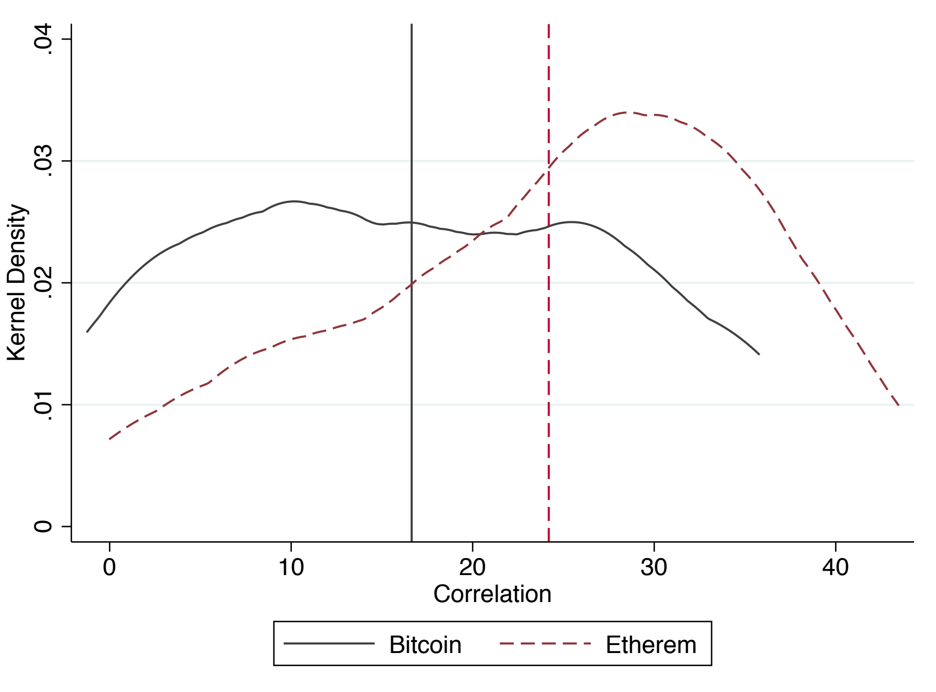
Figure B.11: Perceived Corruption and Trust



Notes: This figure plots the relationship between trust and the perceived corruption control in business, civil service, the local government, and the state government. The trust measure is from the Global Preference Survey, and the corruption control scores are calculated from the Global Value Survey.

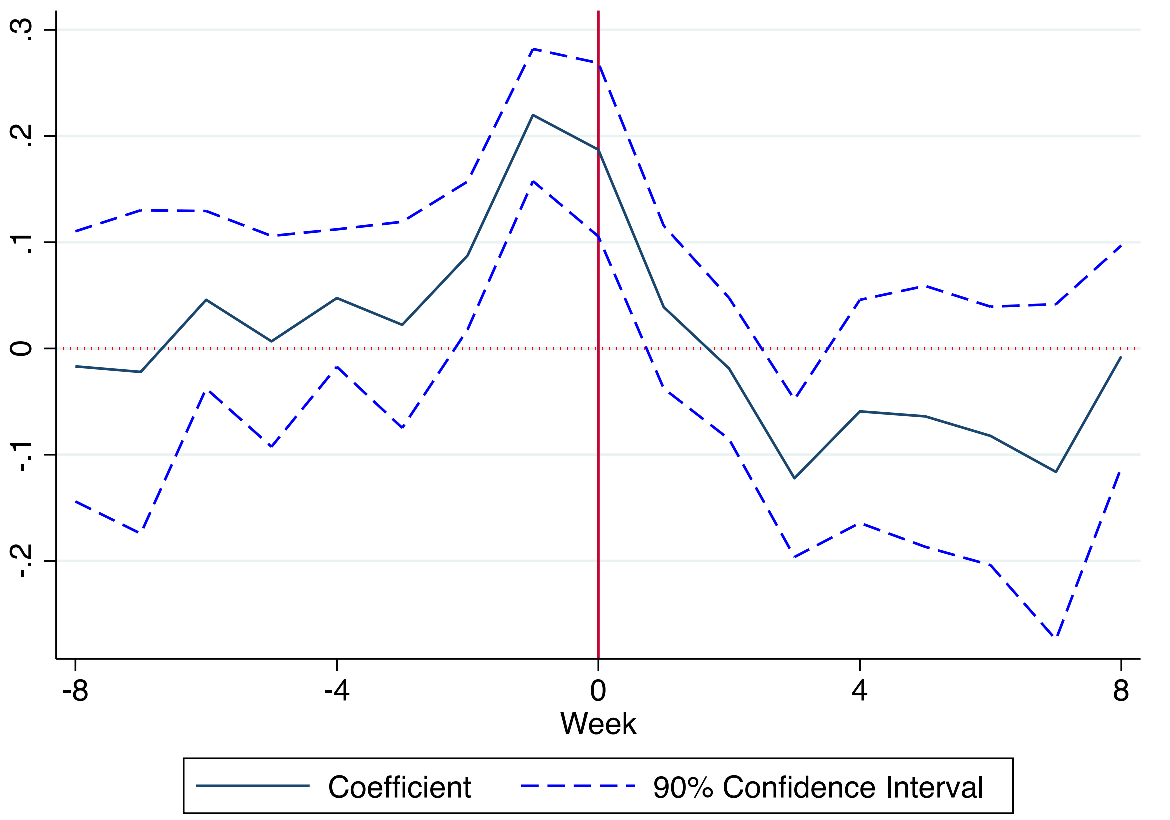
$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Figure B.12: Kernel Density of Correlation between Returns of Stock and Crypto



Notes: This figure plots the kernel density of the correlation between stock index returns and cryptocurrency US dollar returns. The black solid vertical line indicates the average correlation between domestic stock returns and Bitcoin returns. The red dashed vertical line represents the average correlation between domestic stock returns and Ethereum returns.

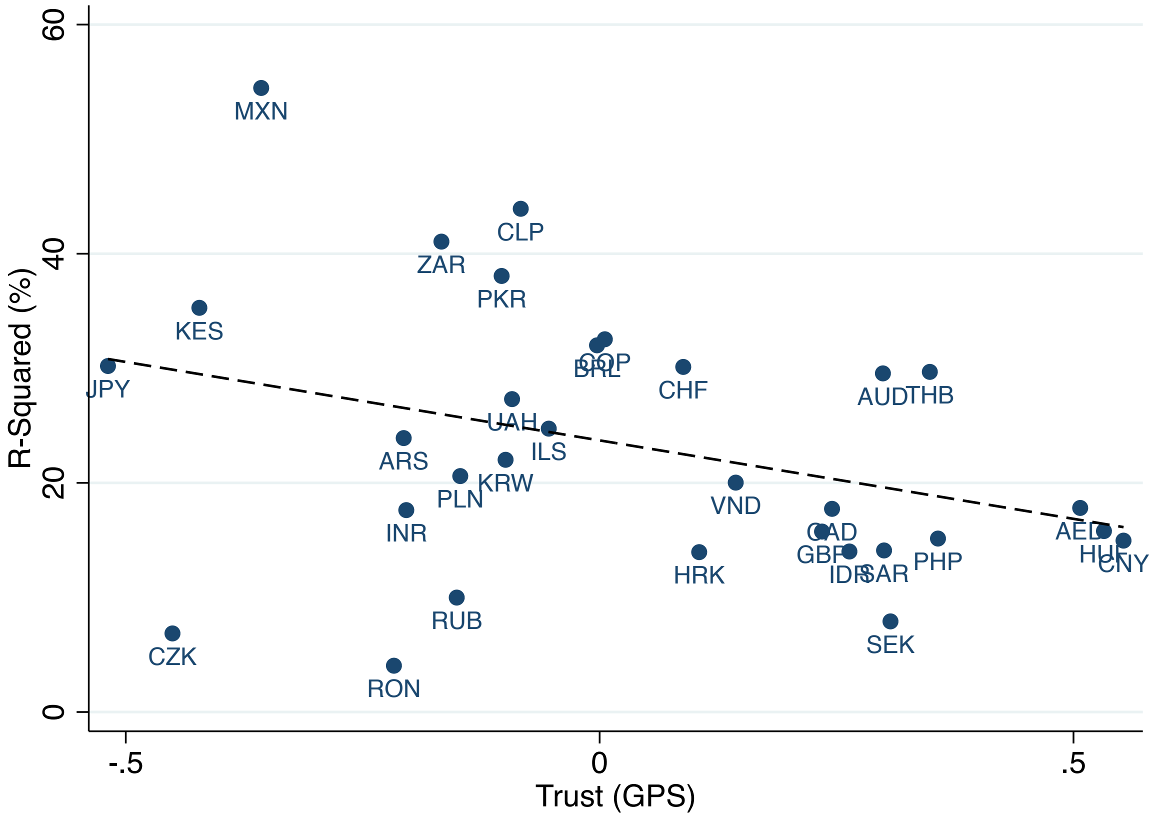
Figure B.13: Exchange Rate and Price Deviation



Notes: This figure plots coefficients $\beta_{c,t}$ in uni-variate regressions of price deviations on lead-lag exchange rate return.

$$Deviation_{c,t} = \beta_{c,t+i} Ret^{Currency}_{c,t+i} + \gamma_c + \epsilon_{c,t}$$

Figure B.14: In-sample R-squared and Trust

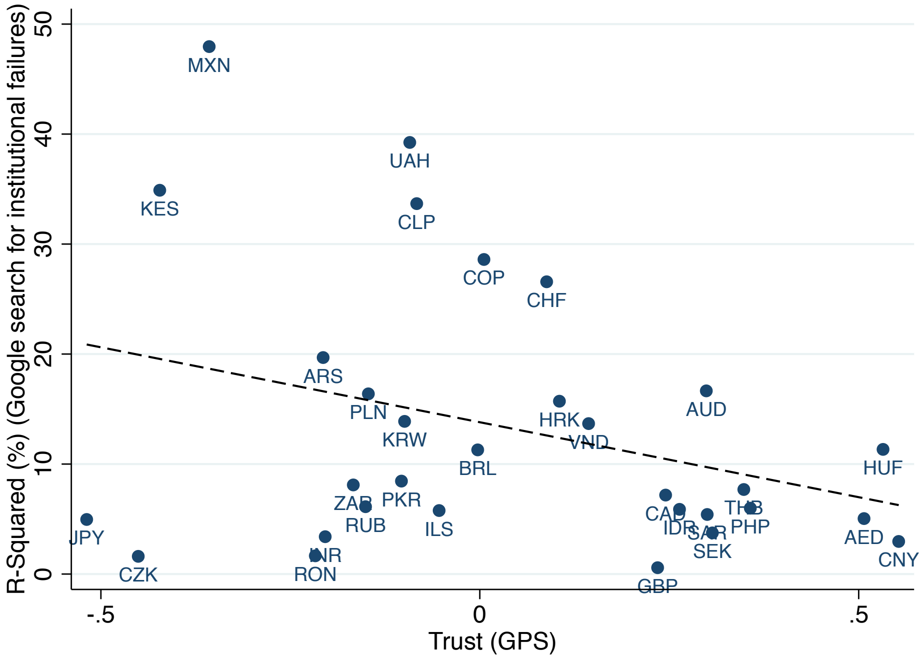


Notes: This figure plots the R-Squared obtained from the following regressions for each country against their trust levels.

$$\widehat{Deviation_t} = \alpha + \sum_{i=1}^{8} \beta X_{i,t} + \epsilon_t$$

where the eight factors include four Google search indices for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Figure B.15: In-sample R-squared and Trust (Google Search for Institutional Failures)

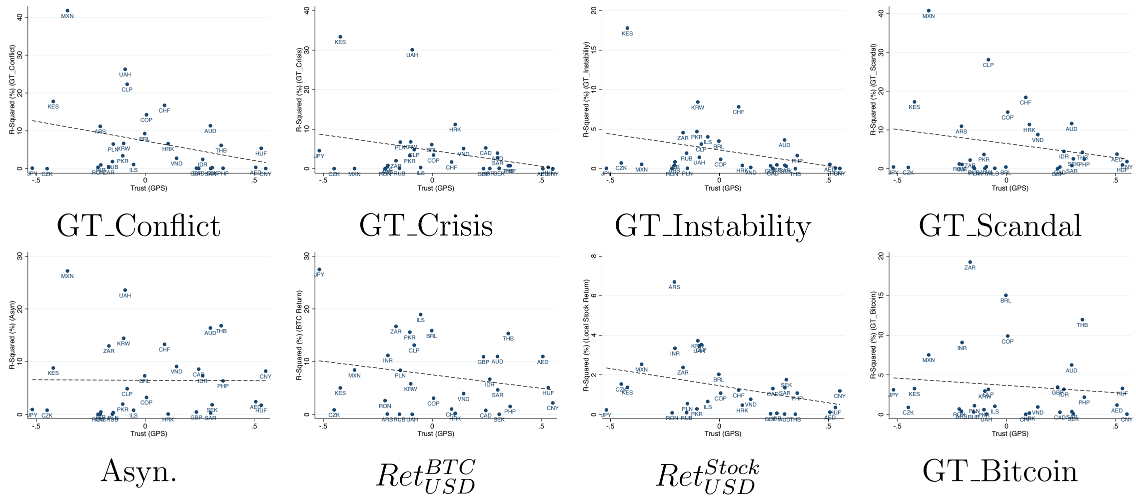


Notes: This figure plots the R-Squared obtained from the following regressions for each country against their trust levels.

$$\widehat{Deviation_t} = \alpha + \sum_{i=1}^{4} \beta X_{i,t} + \epsilon_t$$

where $X_{i,t}$ $(i = 1, 2, 3, 4)$ are the Google searches of keywords "Conflict," "Crisis," "Instability," and "Scandal" only.

Figure B.16: Uni-variate in-sample R-squared and Trust



Notes: This figure plots the R-Squared obtained from the following uni-variate regressions for each country against their trust levels.

$$\widehat{Deviation_t} = \alpha + \beta X_{c,t} + \epsilon_t$$

$X_{i,t}$ denotes each of the eight factors: Google search indices for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Table B.1: Bitcoin Residual Trading Volume and Trust Level

	Residual Log Volume			Residual Volume per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust	-4.560***	-4.373***	-4.828***	-21.40***	-21.19**	-25.86***
	(-3.62)	(-3.05)	(-3.07)	(-2.86)	(-2.48)	(-3.06)
Legal Status		0.432	0.0283		2.180	0.367
		(0.61)	(0.04)		(0.52)	(0.08)
Tax Laws		0.310	-0.390		-2.434	-6.646
		(0.35)	(-0.38)		(-0.46)	(-1.20)
Anti-Money Laundering		0.342	-0.0748		1.959	-0.816
		(0.93)	(-0.17)		(0.89)	(-0.33)
Capital Controls			-0.322			-3.294
			(-0.35)			(-0.66)
Credit			0.0114			0.102**
			(1.69)			(2.81)
R-squared	31.14%	34.40%	40.62%	22.03%	25.05%	47.96%
# Currencies	31	31	28	31	31	28

Notes: This table reports the relationship between trust and residual 2019 Bitcoin trading volume. The residual trading volume is the error term estimated from the following regression:

$$Vol_c = \beta_1 Log(Pop_c) + \beta_2 Log(GDP_c) + \gamma + \widehat{Vol_c}$$

The independent variable is residual 2019 Bitcoin trading volume in Columns (1)-(3), and residual 2019 Bitcoin trading volume per capita in Columns (4)-(6). Columns (1) and (4) reports the results from the uni-variate regression:

$$\widehat{Vol_c} = \beta Trust_c + \gamma + \epsilon_c$$

Columns (2) and (5) include three variables on cryptocurrency regulations: legal status, tax laws, and anti-money laundering regulations. Columns (3) and (6) add capital controls and credit by financial sector (% GDP) in the regressions. Three countries are missing in Columns (3) and (6): the United Arab Emirates and Croatia do not have data in capital controls, Canada does not provide credit data in World Development Indicators. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Correlation Matrix of Cumulative Google Search Indices

	Conflict	Crisis	Instability	Scandal
Conflict	100%			
Crisis	19.32%	100%		
Instability	48.58%	-3.57%	100%	
Scandal	11.73%	7.80%	-10.21%	100%
Mean	188.11	148.32	127.32	165.24
S.D.	65.06	59.22	67.45	55.06

Notes: This table reports the correlation, mean, and standard deviation of cumulative Google search indices of four keywords: "conflict," "crisis," "instability," and "scandal". The raw indices range from 0 to 100. The maximum score is set as 100 by Google. The cumulative Google search index is defined as the eight-week discounted sum with a rate of 0.8:

$$GT_{c,t} = \sum_{i=0}^{i=7} 0.8^i \times Google_{c,t-i}$$

where $GT_{c,t}$ is the cumulative Google Trend index in country c, and $Google_{c,t}$ denote the raw weekly Google Trend index.

Table B.3: Shortlisted Events of Google Search Spikes

Country	Period	Keyword	Event
Brazil	Dec 2017	Crisis	Standard and Poor's reduces Brazil's credit rating from BB to BB-
Korea	Oct 2016	Scandal	Widespread coverage of 2016 South Korean political scandal began
Indonesia	Dec 2017	Conflict	Mimika blockade: Tensions developed in Mimika Regency of Papua
Poland	Nov 2017	Crisis, Conflict, Instability	White nationalists call for ethnic purity at Polish demonstration
Chile	Oct 2019	Crisis	Civil protests have taken place throughout Chile
Russia	Dec 2017	Conflict	The Russian military intervention in the Syrian Civil War
Russia	Oct 2018	Instability	Nuclear missiles tensions between US and Russia are placed in Europe
Russia	Feb 2017	Scandal	Donald Trump's Russia scandal got started
Japan	Feb 2017	Scandal	The land sale scandal of central government of Japan
UK	May 2018	Scandal	The 2018 Windrush scandal & Jeremy Hunt property scandal
UK	Sep 2015	Scandal	Prime Minister Cameron's drug and honesty scandal
Brazil	Feb & Mar 2015	Crisis, Scandal	Petrobras corruption scandal
Argentina	May & Sep 2018	Crisis	Argentine monetary crisis
Mexico	Oct & Nov 2016	Crisis	Trump's election and policy
Ukraine	Feb 2014	Crisis, Conflict	Political crisis & Change of hryvnia as floating currency
Colombia	Aug 2015	Crisis	Oil price decline & Colombian peso depreciation
Russia	Mar 2014	Crisis	Oil price decline & International sanction & Political rent

Notes: A shortlist of events matched with peaks in Google Trends. In total, 121 surges emerge in the four keywords: Conflict, Crisis, Instability, and Scandal. 95 surges can be found with concrete events, while we cannot tie events to the other 26 spikes. See Appendix **??** for the full list.

Table B.4: Robustness: Price Deviation Response to Institutional Failures

	Dependent Variable: *Deviation* (bps)			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	2.617**	1.216*	2.173**	1.951***
	(2.64)	(1.90)	(2.43)	(2.76)
$Ret^{BTC}_{USD,t-9\to t-1}$	145.9***	153.6***	165.1***	165.3***
	(3.06)	(3.30)	(3.54)	(3.60)
$Ret^{Currency}_{c,t-9\to t-1}$	732.5	645.3	636.9	544.7
	(1.69)	(1.44)	(1.48)	(1.29)
# observations	7,843	7,843	7,843	7,843

Notes: This table reports the robustness check. Bitcoin 8-week returns and currency exchange rate 8-week returns are included in the panel regression. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Ret^{BTC}_{USD,t-9\to t-1} + \beta_3 Ret^{Currency}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google search indices of four keywords: "conflict," "crisis," "instability," and "scandal".

Table B.5: Robustness: Attention to Bitcoin and Institutional Failures

	Dependent Variable: $\Delta GT\_Bitcoin_t$			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	0.0711***	0.0716***	0.0589***	0.0348***
	(5.02)	(3.79)	(3.48)	(3.49)
$Ret^{BTC}_{USD,t-9\to t-1}$	42.35***	42.34***	42.92***	42.88***
	(31.78)	(31.41)	(31.53)	(30.93)
$Ret^{Currency}_{c,t-9\to t-1}$	-29.56	-30.83	-31.61	-33.96
	(-1.27)	(-1.29)	(-1.42)	(-1.48)
$Ret^{Stock}_{c,t-9\to t-1}$	3.031	3.064	2.891	3.717
	(0.65)	(0.68)	(0.71)	(0.82)
# observations	7,688	7,688	7,688	7,688

Notes: This table reports the response of "Bitcoin" Google search growth to four institutional failures ("Conflict," "Crisis," "Instability," and "Scandal") controlling for past eight-week Bitcoin returns, past eight-week currency returns, and past eight-week stock market returns.

$$\Delta GT\_Bitcoin_{c,t} = \beta_1 GT_{c,t} + \beta_2 Ret^{BTC}_{USD,t-9\to t-1} + \beta_3 Ret^{Currency}_{c,t-9\to t-1} + \beta_4 Ret^{Stock}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Attention to"Gold" and Institutional Failures

	Dependent Variable: *GT_Gold*			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	0.0202	0.0125	0.0126	-0.0116
	(1.40)	(1.38)	(1.18)	(-1.39)
# observations	7,688	7,688	7,688	7,688

Notes: This table reports regressions of Google searches of keyword "Gold" on the cumulative Google search indices: "Conflict" in Column (1), "Crisis" in Column (2), "Instability" in Column (3), and "Scandal" in Column (4).

$$GT\_Gold_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Robustness: Heterogeneous Response to Google Trend

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$GT\_Conflict$	1.323**	0.0166	2.515	2.510**	-2.919*
	(2.07)	(0.05)	(1.31)	(2.77)	(-2.02)
$GT\_Conflict \times Distrust$					4.494**
					(2.59)
$GT\_Instability$	2.133**	2.415	1.229	2.721*	3.486
	(2.38)	(1.32)	(0.75)	(2.18)	(0.83)
$GT\_Instability \times Distrust$					-1.377
					(-0.35)
$GT\_Scandal$	1.713***	1.187***	2.739***	1.485***	1.439
	(8.39)	(4.55)	(5.88)	(4.30)	(1.40)
$GT\_Scandal \times Distrust$					1.196***
					(4.03)
# observations	7,843	2,783	2,277	2,783	7,843
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to Google searches in "Crisis", "Instability", and "Scandal", and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Table. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

Table B.8: Horsing Racing with Other Country Features

	Dependent Variable: *Deviation*					
Covariate	(1) N/A	(2) GDP	(3) Credit	(4) Law	(5) Gov Eff	(6) Corruption
GT_Crisis	-5.469**	-3.564***	-4.099***	-4.700***	-4.748***	-4.797***
	(-2.32)	(-4.09)	(-3.52)	(-4.18)	(-4.34)	(-4.22)
GT_Crisis × *Distrust*	8.530***	6.874***	5.679***	4.521***	4.557***	4.459***
	(2.95)	(3.04)	(3.15)	(4.10)	(3.95)	(4.22)
GT_Crisis × *Covariate*		-0.311	-0.013	-0.412	-0.328	-0.224
		(-1.53)	(-1.09)	(-0.47)	(-0.35)	(-0.32)
# observations	7,843	7,843	7,590	7,843	7,843	7,843

Notes: This table reports the horse-racing of trust with other country features, including GDP per capita, credit by the financial sector, the rule of law, government effectiveness, and corruption control scores.

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \beta_3 Covariate \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google Trend index on the keywords of institutional failures. Robust standard errors are clustered at the currency level. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Price Deviation Response to Ethereum Return

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Ret^{ETH}_{USD,t-9\to t-1}$	0.212	-0.0974	0.308	0.444**	-0.896**
	(1.43)	(-0.43)	(0.85)	(2.40)	(-2.05)
$Ret^{ETH}_{USD,t-9\to t-1} \times Distrust$					1.146***
					(2.95)
# observations	6,973	2,475	2,023	2,475	6,973
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to the past eight-week Ethereum return and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Ret^{ETH}_{USD,t-9\to t-1} + \beta_2 Distrust_c \times Ret^{ETH}_{USD,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

Table B.10: Return Asynchronization and Capital Controls

	Dependent Variable: Return Asynchronization					
	Capital Controls		Retail Transfer Costs			
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Controls	7.504*					
	(1.95)					
i.Gate		10.22				
		(1.60)				
i.Wall		15.40*				
		(1.97)				
Exchange Rate Margin			0.873		-2.288	
			(0.45)		(-0.78)	
Transaction Fee				-0.583		-0.285
				(-0.49)		(-0.62)
R-squared	12.38%	13.34%	0.76%	0.88%	5.75%	3.67%
# Currencies	29	29	29	29	12	12

Notes: This table reports the impacts of capital controls and retail money transfer costs on return asynchronization. The capital control measure is from Fernández et al. (2016): In Column (1), we assign 1 to "Open" category, 2 to "Gate" category, and 3 to "Wall" category. In Column (2), the "Open" category is the missing group; i.Gate and i.Wall are two indicators for the "Gate" and "Wall" categories. Retail transfer costs are collected from Monito.com and the World Bank remittance survey. Column (3) - (4) report the results based on data from Monito.com, and Column (5) - (6) report the results based on data from World Bank remittance survey. The exchange rate margin refers to the markup paid to the service provider per unit of fund transferred. The transaction fee refers to the fixed cost per transaction charged by the service provider.

$$\overline{Asyn_c} = \beta X_c + \gamma + \epsilon_c$$

where $\overline{Asyn_c}$ is the average return asynchronization in country c, and X_c refers to capital control or retail transfer cost. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11: Return Asynchronization and Regulations

	Return Asynchronization (%)			
	(1)	(2)	(3)	(4)
Regulate or not	-13.50***			
	(-3.34)			
Legal Status		5.712**		
		(2.12)		
Tax Laws			-7.202*	
			(-1.88)	
Anti-Money Laundering				-2.984
				(-0.72)
# Currencies	31	25	25	25

Notes: This table reports the relationship between return asynchronization and regulations. We classify the regulatory status into four categories. "Regulate or not" dummy is one if the country has any specific regulation for cryptocurrency; otherwise, zero. "Legal Status" dummy is one if regulators ban cryptocurrency; otherwise, zero. "Tax Laws" dummy is one if tax laws apply to cryptocurrency; otherwise, zero. "Anti-Money Laundering" dummy is one if the country announces anti-money laundering laws for cryptocurrency; otherwise, zero.

$$\overline{Asyn_c} = \beta Law_c + \epsilon_c$$

where $\overline{Asyn_c}$ is the average return asynchronization in country c. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12: Trust and Confidence in Institutions

	(1) Bank	(2) Company	(3) Government	(4) Politics	(5) Civil Service	(6) Justice
Trust	112.7**	50.83**	128.1***	108.1**	117.0***	119.3***
	(2.40)	(2.10)	(3.05)	(2.59)	(3.69)	(3.11)
R-squared	24.21%	15.03%	27.12%	21.17%	35.29%	28.72%
# Currencies	20	27	27	27	27	26

Notes: This table reports the relationship between trust and confidence in institutions, including banks, companies, government, politics, civil service, and justice. The trust measure is from the Global Preference Survey, and the confidence scores are calculated from the Global Value Survey. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Confidence_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Table B.13: Trust and Corruption in Institutions

	(1) Business	(2) Civil Service	(3) Local Gov.	(4) State Gov.
Trust	65.17**	85.10**	100.9**	69.73*
	(2.15)	(2.18)	(2.25)	(1.92)
R-squared	23.49%	24.10%	25.22%	19.68%
# Currencies	17	17	17	17

Notes: This table reports the relationship between trust and the perceived corruption control in business, civil service, the local government, and the state government. The trust measure is from the Global Preference Survey, and the corruption control scores are calculated from the World Value Survey. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Table B.14: Trust Validation

	(1) Most Trusted	(2) Know Personally	(3) Neighbors	(4) First Met
Trust	20.92*	67.13*	60.38**	46.24
	(2.01)	(1.96)	(2.31)	(1.51)
R-squared	13.43%	15.47%	20.31%	9.78%
# observations	17	17	17	17

Notes: This table validates the correlation between trust in the Global Preference Survey (GPS) and trust variables in the World Value Survey (WVS):

$$Trust_c^{WVS} = \beta Trust_c^{GPS} + \alpha + \epsilon_c$$

WVS's trust measures include general trust in most people, trust people you know personally, trust in your neighbors, and trust people you first met. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.15: Correlation between Crypto Returns and Stock Returns

	Dependent Variable: $Ret^{Crypto}_{t-9\to t-1}$			
	Weekly		Monthly	
	BTC	ETH	BTC	ETH
	(1)	(2)	(3)	(4)
$Ret^{Stock}_{c,t-9\to t-1}$	0.239***	0.494***	1.394**	2.922**
	(4.94)	(4.65)	(2.15)	(2.02)
# observations	8,176	6,965	264	225
$Asyn_c$	5.45%	5.56%	13.18%	13.39%

Notes: This table reports uni-variate regressions of log stock returns on log BTC/ETH returns in the past eight weeks. Columns (1) and (2) estimate with panel data (at currency by week level). Columns (3) and (4) estimate with time-series data (equal-weighted collapsing stock returns to obtain weekly data). Raw correlations are reported for each specification. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Ret^{Crypto}_{t-9\to t-1} = \beta Ret^{Stock}_{c,t-9\to t-1} + \epsilon_{c,t}$$

Table B.16: Price Deviation Regressions with Currency Return Controls

	Dependent Variable: $Deviation_{c,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GT_Crisis	2.678**	2.687**						
	(2.71)	(2.71)						
$Asyn_c$			5.999***	6.038***				
			(4.69)	(4.70)				
$Ret^{BTC}_{USD,t-9\to t-1}$					119.4**	115.3**		
					(2.75)	(2.67)		
$Ret^{Stock}_{c,t-9\to t-1}$							237.8**	223.1**
							(2.24)	(2.11)
$Ret^{Currency}_{c,t}$		1787.8***		2045.3***		1784.4***		1836.5***
		(3.81)		(3.98)		(3.85)		(3.71)
$Ret^{Currency}_{c,t-1}$		2255.0***		2207.9***		1876.3***		1940.1***
		(4.93)		(5.43)		(4.41)		(4.61)
# observations	7,843	7,843	8,060	8,060	8,060	8,060	8,060	8,060

Notes: This table examines the impacts of exchange rate on main specifications. Columns (1), (3), (5), and (7) report uni-variate regressions on $X_{c,t}$: Google Trend index of keyword "Crisis", return asynchronization, Bitcoin past 8-week returns, and local stock 8-week returns. In Columns (2), (4), (6), and (8), we add simultaneously, and one-week lagged exchange rate returns as the following:

$$Deviation_{c,t} = \beta X_{c,t} + \kappa_1 Ret^{Currency}_{c,t} + \kappa_2 Ret^{Currency}_{c,t-1} + \gamma_c + \epsilon_{c,t}$$

t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.17: Predictability in FX Exchange Rates

	Dependent Variable: $FX_{c,t}$				
	(1) CIP	(2) 1-week FX Ret	(3) 8-week FX Ret	(4) 24-week FX Ret	(5) Dummy (24-week Ret < -15%
$Deviation_{c,t}$	3.06×10^{-8}	0.00427	-0.00447	-0.0296	5.77×10^{-6}
	(0.35)	(0.71)	(-0.80)	(-1.18)	(1.00)
# observations	4,420	8,029	7,812	7,316	7,316

Notes: This table explores whether price deviations predict anything in the FX market.

$$FX_{c,t} = \beta Deviation_{c,t} + \gamma_c + \epsilon_{c,t}$$

$FX_{c,t}$ stands for Libor-based deviations from covered interest parity (CIP) in Column (1), the future one-week exchange rate return in Column (2), the future 8-week exchange rate return in Column (3), the future 24-week exchange return in Column (4), and the dummy for massive currency depreciation in next 24 weeks (24-week Ret < -15%) in Column (5). The construction of CIP deviation follows Du et al. (2018). The Libor basis is equal to:

$$y_{t,t+n}^{USD,Libor} - (y_{t,t+n}^{c,Libor} - \rho_{t,t+n})$$

where $n =$ three months, $y_{t,t+n}^{USD,Libor}$ and $y_{t,t+n}^{c,Libor}$ denote the US and foreign three-month Libor rates, and $\rho_{t,t+n} \equiv \frac{1}{n}(f_{t,t+n} - s_t)$ denotes the forward premium obtained from the forward $f_{t,t+n}$ and the spot s_t exchange rates. With Bloomberg data, we can construct CIP deviations for 17 out of 31 countries. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.18: In-sample R-Squared Analysis (Individual factor)

	Dependent Variable: $\widehat{Deviation}$			
	(1) All Countries	(2) High-trust	(3) Medium-trust	(4) Low-trust
$GT\_Conflict$	1.66%	0.00615%	5.94%	2.81%
GT_Crisis	0.429%	0.0389%	0.659%	1.35%
$GT\_Instability$	0.16%	0.121%	0.132%	0.244%
$GT\_Scandal$	1.41%	0.126%	4.68%	1.18%
$Asyn_c$	2.82%	3.04%	7.64%	0.0499%
$Ret^{BTC}_{USD,t-9\to t-1}$	2.24%	0.486%	2.71%	4.85%
$Ret^{Stock}_{c,t-9\to t-1}$	0.161%	0.0388%	0.12%	1.68%
$GT\_Bitcoin$	0.655%	0.0253%	1.25%	1.61%
Average	1.192%	0.485%	2.891%	1.722%
# observations	7,645	2,722	2,225	2,698

Notes: This table reports the R-Squared of the investment factor analysis on price deviation for all coutries, high-trust countries, medium-trust countries, and low-trust countries:

$$\widehat{Deviation_{c,t}} = \beta X_{c,t} + \gamma + \epsilon_t$$

where $\widehat{Deviation_{c,t}}$ is the demeaned price deviation by each country c, and $X_{c,t}$ denotes each of the eight factors: four Google searches of institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Table B.19: In-sample R-Squared Analysis (Multi-factor)

	Dependent Variable: $\widehat{Deviation}$				
	(1)	(2)	(3)	(4)	(5)
$Asyn_c$	2.794***	2.574***	2.711***	2.709***	2.745***
	(13.03)	(11.73)	(12.49)	(12.47)	(12.64)
$GT\_Conflict$		0.455***	0.383***	0.382***	0.399***
		(4.21)	(3.58)	(3.57)	(3.73)
GT_Crisis		0.0939	0.0326	0.0314	0.0339
		(0.92)	(0.32)	(0.31)	(0.34)
$GT\_Instability$		0.122	0.171	0.170	0.155
		(1.11)	(1.57)	(1.56)	(1.43)
$GT\_Scandal$		0.672***	0.687***	0.687***	0.677***
		(5.99)	(6.19)	(6.19)	(6.11)
$Ret^{BTC}_{USD,t-9\to t-1}$			199.7***	197.4***	196.5***
			(13.70)	(12.06)	(12.01)
$GT\_Bitcoin$				0.0526	0.0471
				(0.30)	(0.27)
$Ret^{Stock}_{c,t-9\to t-1}$					212.2***
					(3.90)
R^2	0.0282	0.0393	0.0617	0.0617	0.0635
# observations	7,645	7,645	7,645	7,645	7,645

Notes: This table reports the multi-factor analysis on price deviation for all 31 countries:

$$\widehat{Deviation}_{c,t} = \sum_i \beta X^i_{c,t} + \gamma + \epsilon_t$$

where $\widehat{Deviation}_{c,t}$ is the demeaned price deviation by each country c, and $X^i_{c,t}$ denotes each of the eight factors: four Google search for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Table B.20: Price Deviation Response to Realized Volatility

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Vol_{c,t-9\to t-1}$	0.0868***	0.0668**	0.148	0.0866***	0.0316
	(3.34)	(2.34)	(1.72)	(3.25)	(0.49)
$Vol_{c,t-9\to t-1} \times Distrust$					0.0701
					(1.22)
# observations	9620	2860	2340	2860	8060
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to the past eight-week realized volatility of Bitcoin return and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Vol^{BTC}_{c,t-9\to t-1} + \beta_2 Distrust_c \times Vol^{BTC}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

Table B.21: Price Deviation Response to Return Skewness

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Skew_{c,t-9\to t-1}$	0.0333	-0.0437	0.0789*	-0.0140	-0.118
	(1.16)	(-0.86)	(1.90)	(-0.46)	(-1.13)
$Skew_{c,t-9\to t-1} \times Distrust$					0.127
					(1.34)
# observations	9571	2860	2315	2836	8011
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to the past eight-week skewness of Bitcoin return and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 Skew^{BTC}_{c,t-9\to t-1} + \beta_2 Distrust_c \times Skew^{BTC}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

B.2 For Online Publication: Theory Appendix

B.2.1 Proof of Proposition 1: Local Risky Weight

We consider the two-asset case: investors choose the optimal share of wealth to invest in the local risk asset by solving the following utility maximization problem:

$$\begin{aligned}
\max_{\pi_{L,t}} logE_t[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}] &= \max_{\pi_{L,t}} log\{E[p\frac{W_c^{1-\gamma}}{1-\gamma} + (1-p)\frac{W_{nc}^{1-\gamma}}{1-\gamma}]\} \\
&= \max_{\pi_{L,t}} log\{E_t[pe^{(1-\gamma)w_{t+1,c}} + (1-p)e^{(1-\gamma)w_{t+1,nc}}]\} \\
&= \max_{\pi_{L,t}} log\{E_t[pe^{(1-\gamma)r_{p,t+1,c}} + (1-p)e^{(1-\gamma)r_{p,t+1,nc}}]\} \\
&= \max_{\pi_{L,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,nc}}[1-p+pe^{(1-\gamma)(r_{p,t+1,c}-r_{p,t+1,nc})}]\} \\
&= \max_{\pi_{L,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,nc}}[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&= \max_{\pi_{L,t}} logE_t e^{(1-\gamma)r_{p,t+1,nc}} + logE_t[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&= \max_{\pi_{L,t}} logE_t e^{(1-\gamma)r_{p,t+1,nc}} + logE_t[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&\approx \max_{\pi_{L,t}} \underbrace{\pi_{L,t}(\mu_L - r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_L^2 + \frac{1}{2}(1-\gamma)\pi_{L,t}^2\sigma_L^2}_{\text{Financial Component}} + \underbrace{p[\pi_{L,t}(\bar{b}+\frac{1}{2}\sigma_b^2) - \frac{1}{2}\gamma\pi_{L,t}^2\sigma_b^2]}_{\text{Trust Component}}
\end{aligned}$$

The first part is the optimization problem purely from the financial component, and the second part comes from the distrust loss. Then, we can solve the optimal investment in the local risky asset:

$$\pi_{L,t} = \frac{\mu_L - rf_L + \frac{1}{2}\sigma_L^2 + p(\bar{b}+\frac{1}{2}\sigma_b^2)}{\gamma(\sigma_L^2 + p\sigma_b^2)}$$

In the derivation, we use $w_{t+1,nc} = r_{p,t+1,nc} + w_t$, $w_{t+1,c} = r_{p,t+1,c} + w_t$, and the difference between portfolio returns in the cheat and non-cheat states can be derived with the following approximations:

$$r_{p,t+1,nc} - r_{f,t+1} = log(1+\pi_{L,t}(exp(r_{L,t+1}-r_{f,t+1})-1)) \approx \pi_{L,t}(r_L - r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_L^2$$

$$r_{p,t+1,c} - r_{f,t+1} \approx log(1+\pi_{L,t}(exp(r_{L,t+1}+b-r_{f,t+1})-1)) \approx \pi_{L,t}(r_L+b-r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})(\sigma_L^2+\sigma_b^2)$$

$$r_{p,t+1,c} - r_{p,t+1,nc} = \pi_{L,t} b + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2$$

B.2.2 Proof of Proposition 2: Global and Local Risky Weights

We extend the framework into the multiple risky assets:

$$\max_{\pi_t} \pi_t'(\boldsymbol{r}_{t+1} - rf_{t+1})\boldsymbol{\iota} + \frac{1}{2}\pi_t'\boldsymbol{\sigma}_t^2 - \frac{1}{2}\pi_t'\boldsymbol{\Sigma}\pi_t + \frac{1}{2}(1-\gamma)\pi_t'\boldsymbol{\Sigma}\pi_t + \pi_t'\boldsymbol{p}\bar{\boldsymbol{b}} + \frac{1}{2}(1-\gamma)\pi_t'\boldsymbol{\sigma}_b^2\boldsymbol{p}\pi_t]$$

π_t is a vector of wealth share invested by asset. $\boldsymbol{\Sigma}$ is the *conditional* variance-covariance matrix, $\boldsymbol{r}_{t+1}$ is the vector of returns, $\boldsymbol{p}$ and $\boldsymbol{\sigma}_b^2$ are diagonal matrices with the cheating probability and the variance of cheating magnitude for each asset, $\bar{\boldsymbol{b}}$ is a vector of average cheating magnitude for each asset, ι is a vector of ones.

The optimal portfolio holdings

$$\pi_t = \frac{1}{\gamma}(\boldsymbol{\Sigma} + \boldsymbol{\sigma}_b^2)^{-1}[\boldsymbol{r}_{t+1} + \boldsymbol{p}\bar{\boldsymbol{b}} - rf_{t+1}\boldsymbol{\iota} + \frac{1}{2}(\boldsymbol{\sigma}_t^2 + \boldsymbol{\sigma}_b^2\boldsymbol{p})]$$

Particularly, we are interested in the case with one local risky asset and one global risky asset:

$$\pi_t = \begin{bmatrix} \pi_L \\ \pi_G \end{bmatrix} \text{ and } \boldsymbol{p} = \begin{bmatrix} p & 0 \\ 0 & 0 \end{bmatrix}$$

Then, we can express the portfolio weights as the following:

$$\pi_G = \frac{1}{\gamma\sigma_G^2}\frac{(\sigma_L^2 + p\sigma_b^2)\tilde{\mu_G} - \rho\sigma_L\sigma_G\tilde{\mu_L}}{(1-\rho^2)\sigma_L^2 + p\sigma_b^2}$$

$$\pi_L = \frac{1}{\gamma\sigma_G^2}\frac{\sigma_G^2\tilde{\mu_L} - \rho\sigma_L\sigma_G\tilde{\mu_G}}{(1-\rho^2)\sigma_L^2 + p\sigma_b^2}$$

where $\tilde{\mu_G} = \mu_G + \frac{1}{2}\sigma_G^2 - rf_L$, $\tilde{\mu_L} = \mu_L - rf_L + p\bar{b} + \frac{1}{2}(\sigma_L^2 + p\sigma_b^2)$

B.3 For Online Publication: Events of Google Search Peaks

We manually identify the events behind Google search peaks of the four keywords: Conflict, Crisis, Instability, and Scandal. In total, 121 spikes are found for the four keywords to verify whether the google search on "Conflict," "Crisis," "Scandal" and "Instability" reflect investors' concern for local institutional failures. 95 peaks can be found with concrete events, while we cannot identify events for the other 26 peaks. 78 spikes indicate domestic institution failures or crises, while the other 17 spikes are driven by irrelevant events (e.g., sexual scandals). This appendix documents the full list of the events found with our endeavor.

Events of Google Search Peaks

Currency	Keyword	Date	Short Title	Description	Search related
AED	scandal	2015.7	Ambassador 1MDB Scandal	The scandal swirling around a Malaysian state investment fund allegedly defrauded of billions of dollars has entangled the United Arab Emirates ambassador to the USA, according to court and investigative documents reviewed by The Wall Street Journal.	No
ARS	scandal	2019.8	Notebook Scandal	Searching for last year's notebook scandal when election approaching	N/A
AUD	scandal	2017.10.	Parliamentary eligibility crisis	The High Court hands down its judgment in Re Canavan; Re Ludlam; Re Waters; Re Roberts [No 2]; Re Joyce; Re Nash; Re Xenophon. Ludlam, Waters, Roberts, Joyce, and Nash are all ruled ineligible to have been elected.	Yes
AUD	scandal	2018.3-4	Ball-tampering scandal	A cricket scandal surrounding the Australian national cricket team. In March 2018, during the third Test match against South Africa at Newlands in Cape Town, Cameron Bancroft was caught by television cameras trying to rough up one side of the ball with sandpaper to make it swing in flight.	No
BRL	scandal	2018.2	Anti-Corruption Crusade Rot	Allegations of bias have tarnished the investigation against Lula, setting the stage for yet another institutional crisis in the country.	Yes
CAD	scandal	2015.9	VW diesel emissions scandal		No
CAD	scandal	2019.3	Justin Trudeau Political Scandal	A scandal is swirling around Canadian Prime Minister Justin Trudeau and his Liberal Party. It could threaten the political future of the country's leader and the rule of the Liberal Party, seven months ahead of national elections.	Yes
GBP	scandal	2015.9	Cameron's drug and honesty scandal	In September 2015, Lord Ashcroft published a biography of David Cameron, which suggested that the then Prime Minister took drugs regularly and performed an "outrageous initiation ceremony". It also led to questions about the Prime Minister's honesty with party donors' known tax statuses as Lord Ashcroft suggested he had openly discussed his non-domiciled status with him in 2009, earlier than previously thought.	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
GBP	scandal	2016.4	Panama tax-avoidance scandal	Mr Cameron said that the investment was not intended to avoid tax, and that he paid income tax on the dividends, but no capital gains tax as the profit made from the sale was less than the couple's annual tax free allowance.	Yes
GBP	scandal	2018.5	Windrush scandal & Jeremy Hunt property scandal	The 2018 Windrush scandal, involving members of the Windrush generation being wrongly detained, deported, or threatened with deportation which caused the resignation of then Home Secretary, Amber Rudd. Jeremy Hunt breaks government rule in his property scandal.	Yes
HRK	scandal	2015.1			N/A
IDR	scandal	2019.3	Widodo Bribe Scandal	Muhammad Romahurmuziy's arrest for influence-peddling at the religion ministry may mark end of days for Indonesia's second oldest political party.	Yes
ILS	scandal	2015.9			N/A
INR	scandal	2016.8	Journalist murdered after political scandal	The IJU president SN Sinha said: "He was killed because of his reports exposing unsavory deeds of some powerful politicians and their kin. The police should thoroughly investigate the case and book all those behind his murder instead of arresting some who wielded their knives to kill him, however big or well connected they might be."	Yes
JPY	scandal	2016.3			N/A
JPY	scandal	2017.2	Government land sale scandal	On February 9, 2017, scandal began when Asahi Shimbun reported that the central government of Japan had sold the 8,770 square metres (94,400 sq ft) property in Toyonaka, Osaka Prefecture, to Moritomo Gakuen for around ¥134 million, about 14% of the land's estimated value	Yes
KES	scandal	2018.5-6	Kenyan Anti-corruption drive	Kenyan authorities have detained more than 50 top officials and executives after widespread public anger prompted by allegations of the theft of more than $100m (£75m) at government agencies.	Yes
KRW	scandal	2016.10-11	South Korean political scandal	The 2016 South Korean political scandal involves the influence of Choi Soon-sil, the daughter of shaman-esque cult leader Choi Tae-min, over President Park Geun-hye of South Korea	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
KRW	scandal	2019.3	K-Pop Sex Scandal	Seungri, formerly a member of South Korean boy band Big Bang, is seen arriving at a Seoul police station on March 14, 2019.	No
MXN	scandal	2015.9	VW diesel emissions scandal		No
MXN	scandal	2019.3	Odebrecht Corruption	Mexico has shown a lethargic approach to the Odebrecht scandal. The only high-profile name being investigated for the largest corruption scandal to rock Latin America is Emilio Lozoya Austin. The former president of the state-owned oil company Petróleos Mexicanos (Pemex), who served under former President Enrique Peña Nieto, is accused of conducting a corruption scheme that involved ghost companies between 2012 and 2016.	Yes
PHP	scandal	2015.7	Iglesia ni Cristo leadership controversy	The 2015 Iglesia ni Cristo leadership controversy is a dispute between senior members of the Christian denomination Iglesia ni Cristo (INC) in the Philippines. In July 2015, it was reported that the INC had expelled some of its ministers, along with high-profile members Felix Nathaniel "Angel" and Cristina "Tenny" Manalo	Yes
PKR	scandal	2015 Aug	Child sexual abuse scandal	Pakistan police accused of downplaying child sexual abuse scandal	No
PKR	scandal	2019 Nov	Spot-fixing scandal	Mohammad Asif apologises for role in spot-fixing scandal	No
RON	scandal	2015.9	VW diesel emissions scandal		No
RON	scandal	2017.6	Romanian protests		Yes
RUB	scandal	2017.2-3	Donald Trump's Russia Scandal		Yes
SAR	scandal	2015.7			N/A
SEK	scandal	2015.9	Swedish jet scandal	Cross-shareholdings have cultivated concentration of power among senior executives	No

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
SEK	scandal	2017.4	Swedish elk-hunting scandal	The chairman of Handelsbanken, often considered one of Europe's most respected banks, has become the latest senior Swedish business figure caught up in the scandal over elk hunting hospitality	No
SEK	scandal	2018.3	Nobel Scandal	A man Is accused of sexual misconduct.	No
SEK	scandal	2018.12	Swedish Academy scandal	Man at centre of Swedish Academy scandal appeals rape conviction to Supreme Court	No
THB	scandal	2016.3	Crackdown on corruption	Deputy Prime Minister Prawit Wongsuwan says the names will be "verified" and in February–March 2016 the crackdown will commence	Yes
UAH	scandal	2017.6	Trump–Ukraine scandal	President Trump, right, meets with then-Ukrainian President Petro Poroshenko at the White House in June 2017.	Yes
VND	scandal	2016.8	Fish Death Scandal	Some suspect the government of going too easy on Formosa to protect the firm's 10.5$billioninvestment.Vietnamhappenstobebuildingits$193.6 billion economy largely on foreign-invested export factories and officials are known for offering incentives to bring them into the country, a reason behind the country's fast GDP growth.	Yes
VND	scandal	2019.3	Food safety scandal	57 Vietnamese kindergarteners catch pork tapeworm in unprecedented food safety scandal	No
ZAR	scandal	2016.5			N/A
ZAR	scandal	2018.1	Gupta brothers' corruption	Lord Hain says report by Hogan Lovell into 'money laundering' at tax agency was a whitewash	Yes
AED	crisis	2017.6	Qatar diplomatic crisis	The Qatar diplomatic crisis began in June 2017, when Saudi Arabia, the United Arab Emirates, Bahrain, Egypt, the Maldives, Mauritania, Senegal, Djibouti, the Comoros, Jordan, the Tobruk-based Libyan government, and the Hadi-led Yemeni government severed diplomatic relations with Qatar and banned Qatar-registered airplanes and ships from utilising their airspace and sea routes along with Saudi Arabia blocking the only land crossing	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
AED	crisis	2019.12	UAE Economy First-ever Drop	The United Arab Emirates' economy is ending a difficult year on a low as business activity slumps to a level not seen in more than a decade. New orders for companies in the second-biggest Arab economy fell for the first time on record in November as the impact of recent price cuts to stimulate demand waned. Output growth and payroll numbers also fell, according to the IHS Markit Purchasing Managers' Index, which tracks the country's non-oil activity.	Yes
" ARS	crisis	2018.8	Argentine monetary crisis	The 2018 Argentine monetary crisis was a severe devaluation of the Argentine Peso, caused by high inflation, an increase in the price of the United States dollar at local markets, and other domestic and international factors. As a result of it, the presidency of Mauricio Macri requested a loan from the International Monetary Fund.	Yes
AUD	crisis	2015.7	Migrant crisis	Australian Prime Minister Tony Abbott has said the refugee and migrant crisis in Europe is proof of the need for tough asylum policies.	Yes
AUD	crisis	2019.12	Australia's bushfire crisis	As the area burned across Australia this fire season pushes beyond five million hectares, an area larger than many countries, stories of destruction have become depressingly familia	No
BRL	crisis	2017.11-12	Sovereign credit rating downgrade		Yes
BRL	crisis	2019.12	Trump's steel tariffs	Finally, December has begun badly on Wall Street, with losses triggered by Donald Trump's tariffs on Brazil and Argentina	Yes
CAD	crisis	2019.12	Climate crisis	the Canadian government is in Madrid telling the world that climate action is its No 1 priority. When they get home, Justin Trudeau's newly re-elected government will decide whether to throw more fuel on the fires of climate change by giving the go-ahead to construction of the largest open-pit oil sands mine in Canadian history.	No
CHF	crisis	2019.12			N/A
CLP	crisis	2019.10	Chilean protests	Civil protests have taken place throughout Chile in response to a raise in the Santiago Metro's subway fare, the increased cost of	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
CNY	crisis	2015.11	Chinese stock market turbulence	The Chinese stock market turbulence began with the popping of the stock market bubble on 12 June 2015 and ended in early February 2016. A third of the value of A-shares on the Shanghai Stock Exchange was lost within one month of the event. Major aftershocks occurred around 27 July and 24 August's "Black Monday". By 8–9 July 2015, the Shanghai stock market had fallen 30 percent over three weeks as 1,400 companies, or more than half listed, filed for a trading halt in an attempt to prevent further losses. Values of Chinese stock markets continued to drop despite efforts by the government to reduce the fall.	Yes
COP	crisis	2015.8	Oil price drop & peso depreciation	Colombian economic growth and the value of the Colombian peso are closely tied to the price of oil. Over the last year, the peso has fallen sharply against the USD and most other major currencies. The Colombian peso has depreciated by close to 40% since the oil price decline and 20% since the end of June 2015. Oil and natural gas are Colombia's single largest export, making up 49% of the total export dollars earned.	Yes
CZK	crisis	2019.12	Protest in Prague	Over 50,000 rally against Czech Prime Minister Babis. They urged Prime Minister Andrej Babis to step down from his post over accusations he misused millions in EU funds.	Yes
GBP	crisis	2017.12	Homelessness crisis	Homelessness in England is a "national crisis" and the government's attitude to tackling it is "unacceptably complacent", a committee of MPs say.	Yes
GBP	crisis	2019.12	Election fallout	Following British Prime Minister Boris Johnson's clear victory on December 12, sights are now set on how Johnson will achieve Brexit and how his government will attempt to heal the deep fractures within British politics.	Yes
HUF	crisis	2017.11-12			N/A
HUF	crisis	2019.12	Political crisis	Viktor Orbán claims to run a 'Christian' government, but one of his former allies has denounced his 'hate-filled' regime	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
ILS	crisis	2019.12	Israeli political crisis	Israeli politics experienced a crisis and stalemate between April 2019 and April 2020. Three Knesset elections were held during the period without a clear victor or alliance. In the Israeli elections of April 2019, the two major parties, Blue and White and Likud, received an equal number of 35 seats. The Likud received a mandate from the president to attempt to form a government, but Chairman Benjamin Netanyahu of the Likud party failed to arrange a majority coalition of 61 seats. The Knesset was dissolved shortly thereafter	Yes
INR	crisis	2017.9	China–India border standoff	The 2017 China India border standoff or Doklam standoff refers to the military border standoff between the Indian Armed Forces and the People's Liberation Army of China over Chinese construction of a road in Doklam near a trijunction border area, known as Donglang, or Donglang Caochang (meaning Donglang pasture or grazing field), in Chinese.	Yes
INR	crisis	2019.12	Severe slowdown	India's gross domestic product (GDP) growth has dropped to 4.5% in the July-September quarter of 2019-20, a free fall from the government's ambitious call for a double-digit growth not so long ago. Propelling India into a $5 tn economic behemoth by 2024-2025 also seems implausible now.	Yes
JPY	crisis	2017.4			N/A
KES	crisis	2019.12	Kenya food crisis	In December, Crisis (IPC Phase 3) and Stressed (IPC Phase 2) outcomes persist due to ongoing recovery from the 2018/19 drought and the negative impact of recent floods and landslides on household food and income sources. From October to December, Kenya experienced one of the wettest short rains seasons on record, with rainfall totals ranging up to 400 percent of average. A second round of floods and landslides in November caused the death of 132 people, displaced 17,000 people, and affected approximately 330,000 people, primarily in West Pokot.	Yes
KES	crisis	2019.6	Drought in Africa	Failed rains across eastern Africa, southern Africa, and the Horn of Africa are seeing another dire season for farmers, increasing food prices and driving up the aid needs of tens of millions of already vulnerable people across the three regions.	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
KES	crisis	2017.6	Kenya election	Over the past five years, Kenyan authorities have consistently failed to adequately investigate a range of abuses across the country and undermine basic rights to free expression and association. Human rights activists and journalists face numerous obstacles and harassment.	Yes
KRW	crisis	2019.12	North Korea pressure	The North said it conducted an “important test” at a missile-engine site ahead of a Dec. 31 deadline set by its leader, Kim Jong-un, for a new proposal from Washington on denuclearization.	Yes
MXN	crisis	2019.12	Mexico–Bolivia diplomatic crisis	The 2019–2020 Mexico–Bolivia diplomatic crisis began on 29 October 2019 when the Mexican government congratulated incumbent Bolivian President Evo Morales for his reelection victory.[1] After the election, a preliminary report by the Organization of American States on 9 November reported numerous irregularities in the election, and amid protests and pressure from the Bolivian armed forces and police, Morales was forced to resign	Yes
PHP	crisis	2017.6	Marawi crisis	The Battle of Marawi (Filipino: Labanan sa Marawi), also known as the Siege of Marawi (Filipino: Paglusob sa Marawi) and the Marawi crisis (Filipino: Krisis sa Marawi), was a five-month-long armed conflict in Marawi, Lanao del Sur, Philippines, that started on May 23, 2017, between Philippine government security forces and militants affiliated with the Islamic State of Iraq and the Levant (ISIL), including the Maute and Abu Sayyaf Salafi jihadist groups. The battle also became the longest urban battle in the modern history of the Philippines	Yes
PHP	crisis	2017.11-12	Marawi crisis	The Battle of Marawi (Filipino: Labanan sa Marawi), also known as the Siege of Marawi (Filipino: Paglusob sa Marawi) and the Marawi crisis (Filipino: Krisis sa Marawi), was a five-month-long armed conflict in Marawi, Lanao del Sur, Philippines, that started on May 23, 2017, between Philippine government security forces and militants affiliated with the Islamic State of Iraq and the Levant (ISIL), including the Maute and Abu Sayyaf Salafi jihadist groups. The battle also became the longest urban battle in the modern history of the Philippines	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
PHP	crisis	2019.12	Christmas Typhoon	Christmas Typhoon Leaves 20 Dead in Philippines	No
PKR	crisis	2015.3	India-Pakistan Conflict		Yes
PKR	crisis	2019.12	Balance of payments crisis	Pakistan's main economic storyline in 2019 was austerity. Islamabad implemented belt-tightening measures to ease a balance of payments crisis that hit a peak in October 2018, when Prime Minister Imran Khan, just several months into his term, admitted his country was 'desperate' for loans.	Yes
PLN	crisis	2017.11	Ethnic purity	White nationalists call for ethnic purity at Polish demonstration	Yes
PLN	crisis	2019.12	Leave-EU proposal	Poland could have to leave the EU over its judicial reform proposals, the country's Supreme Court has warned. The proposals would allow judges to be dismissed if they questioned the government's judicial reforms. Judges say the proposals threaten the primacy of EU law and could be an attempt to gag the judiciary.	Yes
RON	crisis	2019.12	No-confidence vote	Romania's government has lost a no-confidence vote, leading to its collapse. A transitional government is now expected to take over until the next national election in 2020.	Yes
RUB	crisis	2017.3-4	Protests suppressing corruption	The 2017–2018 Russian protests were a long series of countrywide street protest actions and demonstrations in the Russian Federation, with the major requirements of: suppressing corruption in the Russian government (from 26 March 2017 till spring 2018); abandoning the planned retirement age hike (from 14 June 2018 till end 2018).	Yes
RUB	crisis	2017.11-12	Protests suppressing corruption	The 2017–2018 Russian protests were a long series of countrywide street protest actions and demonstrations in the Russian Federation, with the major requirements of: suppressing corruption in the Russian government (from 26 March 2017 till spring 2018); abandoning the planned retirement age hike (from 14 June 2018 till end 2018).	Yes
RUB	crisis	2019.5-6			N/A

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
SAR	crisis	2017.11-12	Saudi Arabian purge	A number of prominent Saudi Arabian princes, government ministers, and business people were arrested in Saudi Arabia on 4 November 2017 and the following few weeks after the creation of an anti-corruption committee led by Crown Prince Mohammad bin Salman (also known as MbS).	Yes
SEK	crisis	2019.12			N/A
SEK	crisis	2017.11-12			N/A
THB	crisis	2016.11			N/A
ZAR	crisis	2018.1	Cape Town water crisis	Responsibility for the water supply is shared by local, provincial and national government. The National Water Act (Act 36 of 1998) prescribes that the national government is the ”public trustee” of the nation’s water resources to ensure that water is ”protected, used, developed, conserved, managed and controlled in a sustainable and equitable manner, for the benefit of all persons”. This resulted in tension between the opposition-led local and provincial government (Democratic Alliance, DA) on the one hand, and the majority party-led national government on the other (African National Congress, ANC), with the parties blaming each other for the water crisis.	Yes
ZAR	crisis	2019.12	South African energy crisis	Eskom implemented a further round of load shedding commencing in December 2019. South Africa is currently experiencing its worst energy crisis, when Load Shedding Stage 6 activated for the first time ever in December.[26] Eskom stated that of its total nominal capacity of around 44,000 MW, it was unable to provide around 13,000 MW of total capacity, resulting in the nationwide blackouts.	Yes
AED	conflict	2020.1	Gulf warning	As one leading Iranian figure urged western citizens to “leave the UAE immediately” for their own safety, former Middle East minister Alistair Burt said the US airstrike which killed General Qassim Soleimani was “extremely serious.”	Yes
ARS	conflict	2017.12	Argentina Dirty War	A court in Argentina has granted house arrest to an 88-year-old former police officer who was serving a life sentence for crimes against humanity.	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
BRL	conflict	2017.12	Land conflicts	Deforestation is rife in the Brazilian state of Rondônia, which lies deep in the western Amazon rainforest. A new investigation by Greenpeace reveals that as deforestation of protected areas has risen in the state, so have allegations of attacks against the Indigenous communities that call its disappearing forests home. And as budget cuts deplete resources aimed at protecting these communities, many are worried this violence stands to worsen in the months and years to come.	Yes
CLP	conflict	2016.11			N/A
COP	conflict	2017.4	FARC dissidents	The FARC dissident group was formed in July 2016, when the First Front distanced itself from the FARC negotiations in Cuba. In April 2017, the dissidence formalized its criminal desertion with a public letter expressing “dissatisfaction,” “rejecting” the FARC Secretariat’s “betrayal,” and inviting “all combatants that refuse peace” to join its ranks. Nine dissident fronts, one mobile column and seven urban militias signed the letter. In the letter it was expressed: ”The world should know, that we will continue our fight and that the objective for us is to achieve socialism, through the only alternative, revolution with arms in our hands”.	Yes
CZK	conflict	2015.11-12	Anti-Islam rally	Milos Zeman, the President of the Czech Republic, attended a rally against refugees and Islam in Prague on Tuesday (17 November) on the anniversary of the 1989 Velvet Revolution, which peacefully toppled Communism in then Czechoslovakia.	Yes
CZK	conflict	2016.11-12			N/A
CZK	conflict	2017.12	Rising Czech populism	Far right to gather in Prague as fears grow of rising Czech populism	Yes
IDR	conflict	2015.12	Papuans conflict	10 December 2015, Manokwari, West Papua (Indonesia) — Even in West Papua, the easternmost and least populous province of Indonesia, is torture used to crush and silence. Even there people like Paul Mambrasar have dedicated their lives to fighting it.	Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
INR	conflict	2020.1	India-Pakistan Conflict	Turmoil is never far away in South Asia, between disputed borders, acute resource shortages, and threats ranging from extremist violence to earthquakes. But in 2019, two crises stood out: an intensifying war in Afghanistan and deep tensions between India and Pakistan. And as serious as both were in 2019, expect them to get even worse in the coming year.	Yes
PHP	conflict	2018.8-9			N/A
PHP	conflict	2019.8-9			N/A
PKR	conflict	2020.1	India-Pakistan Conflict	Kashmir question will make the already-dim prospects for a de-escalation in tensions between India and Pakistan even more remote in 2020, raising the chances of conflict between the two South Asian powers.	Yes
PKR	conflict	2016.1	Quetta suicide bombing	A suicide bomber detonated himself near security personal vehicles close to a polio centre in a town near Quetta, Pakistan, killing at least 15 people, including 13 policemen and one soldier killed and wounding another 25, including 18 policemen, two soldiers and six civilians. Both Tehrik-i-Taliban Pakistan and Jaishul Islam organizations claimed responsibility	Yes
PKR	conflict	2015.3	India-Pakistan Conflict		Yes
PKR	conflict	2019.2	India–Pakistan border skirmishes	The 2019 Indo-Pakistan military standoff is a result of a militant attack in February 2019	Yes
PLN	conflict	2017.11	Ethnic purity conflict		Yes
RON	conflict	2017.12	Romanian protests		Yes

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
RON	conflict	2020.1	Ditrău xenophobic incident	The 2020 Ditrău xenophobic incident refers to the incident that started in 26 January 2020 in the village of Ditrău (Hungarian: Ditró), Harghita County, in Romania, in which around 1,800 ethnically Hungarian locals protested the employment of two, later three Sri Lankan workers by the bakery Ditrói Pékség. The locals, led by the chaplain of the village, protested that the bakery's working conditions dissatisfied them and, as well as feared that the immigrants could "impose their culture" and "threaten the Hungarian local ethnic identity".	Yes
RUB	conflict	2017.12	Syrian Civil War	At the end of December 2017, the Russian government said its troops would be deployed to Syria permanently	Yes
THB	conflict	2019.3	Thai election campaign	Far from the idyllic and tourist landscapes of Thailand, the deep south of the country has been mired in a bloody separatist conflict for 15 years, which has remained largely invisible despite resulting in more than 7,000 deaths.	Yes
UAH	conflict	2017.12	Ukraine crisis	Ukraine and separatist rebels in the east of the country have exchanged hundreds of prisoners, in one of the biggest swaps since the conflict began in 2014.	Yes
UAH	conflict	2016.1-2	Ukraine domestic conflict	According to a BBC report in February 2016, Ukraine remained gripped by corruption, and little progress had been made in improving the economy. Low-level fighting continued in the Donbass. The report also said that there was talk of a "Third Maidan" to force the government to take action to remedy the crisis	Yes
VND	conflict	2017.12	USA-Vietnam historical conflict		No
ZAR	conflict	2016.2			N/A
ZAR	conflict	2017.2			N/A
ZAR	conflict	2018.2			N/A
ZAR	conflict	2019.2			N/A
ZAR	conflict	2020.2			N/A

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Search related
BRL	instability	2016.2	Zika virus	World Health Organisation declares a global public health emergency following an outbreak of the Zika virus centred on Brazil.	Yes
CHF	instability	2018.11			N/A
COP	instability	2017.9			N/A
ILS	instability	2020.1	Israeli-Palestinian Conflict	Without progress toward a comprehensive solution, we may see unilateral measures and rising tensions.	Yes
INR	instability	2020.2	Hindu supremacists	For seven decades, India has been held together by its constitution, which promises equality to all. But Narendra Modi's BJP is remaking the nation into one where some people count as more Indian than others.	Yes
MXN	instability	2019.7	Government Rift	The abrupt, door-slamming resignation Tuesday of Mexico's finance minister highlights the difficulty that leftist firebrand President Andrés Manuel López Obrador has found turning his inchoate ideas into economic gains—with potentially dire consequences for a country facing a dearth of investment and a real risk of recession.	Yes
RUB	instability	2017.6-7	Protests suppressing corruption	The 2017–2018 Russian protests were a long series of countrywide street protest actions and demonstrations in the Russian Federation, with the major requirements of: suppressing corruption in the Russian government (from 26 March 2017 till spring 2019)	Yes
SAR	instability	2017.4-5	Strained relations with Iran	The two countries, which stand on opposite sides of the conflicts in Syria and Yemen, are competing for religious and political influence across the Middle East. Saudi Arabia, ruled by a Sunni royal family, is a close ally of the United States and accuses Iran of spreading its revolutionary ideology to destabilize the Arab world. Saudi leaders have taken heart from the Trump administration's criticism of Iran.	Yes
SAR	instability	2019.2	Polarisation instability	The Middle East's polarised and repressive politics will lead to even more instability in the region unless countries take steps to reform and calm tensions, a senior Qatari politician has said.	Yes
SEK	instability	2016.3			N/A
SEK	instability	2019.5			N/A

B.4 For Online Publication: Law and Regulations

We collect the data of the cryptocurrency regulatory framework across countries from the Law Library of Congress. Global Legal Research Directorate at the Law Library of Congress surveys the legal and policy landscape towards cryptocurrency worldwide in 2018. For each country, it documents the progress of cryptocurrency regulation and law. We manually search for the legal status, tax laws, and anti-money laundering laws for every country in our sample. Besides, we collect the announcement dates of cryptocurrency bans, tax laws, and anti-money laundering laws.

In the following table, Column (2) reports the legal status: 1 = implicit ban, 2 = absolute ban, 0 = no info. Column (3) reports tax laws: 1= yes, 0 = no info. Column (4) report anti-money laundering related regulations: 1= warning, 2 = implicit yes, 3= absolute yes, 0= no info. Columns (5)-(8) report the announcement dates of these corresponding regulations.

Law and Regulation

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
AED	2	0	0	Jan, 2017			Under article D.7.3 of the Regulatory Framework for Stored Values and an Electronic Payment System, issued by the Central Bank of the United Arab Emirates in January 2017, all transactions in “virtual currencies” (encompassing cryptocurrencies in Arabic) are prohibited.
ARS	0	1	2		Dec, 2017	Jul, 2014	The amendment to the Income Tax Law on December 29, 2017 provides that the profit derived from the sale of digital currency will be considered income and taxed as such.
AUD	0	1	3		May, 2016	Apr, 2018	The government responded in May 2016 regarding the tax treatment of cryptocurrencies, which noted aspects of the following actions of the Australian Taxation Office (ATO). In the area of anti-money laundering and counterterrorism financing (AML/CTF), the government introduced a bill in Parliament in August 2017 in order bring digital currency exchange providers under the AML/CTF regulatory regime. The bill was enacted in December 2017 and the relevant provisions came into force on April 3, 2018.
BRL	0	0	2				On November 16, 2017, the Brazilian Federal Reserve Bank (Banco Central do Brasil) issued Notice No. 31,379 alerting citizens to the risks arising from the custody and trading operations of virtual currencies.
CAD	0	1	3		Mar, 2017	Jun, 2014	On June 19, 2014, the Governor General of Canada gave his assent to Bill C-31, which includes amendments to Canada’s Proceeds of Crime (Money Laundering) and Terrorist Financing Act. The new law treats virtual currencies, including Bitcoin, as “money service businesses” for the purposes of the anti-money laundering law.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
CHF	0	1	3				In September 2017, FINMA closed down the unauthorized providers of the fake cryptocurrency "E-Coin", liquidated the companies, and issued a general warning about fake cryptocurrencies to investors. Furthermore, three other companies were put on FINMA's warning list due to suspicious activity and eleven investigations were conducted into other presumably unauthorized business models relating to such coins.
CLP	0	0	0				
CNY	1	0	0	Sep, 2017			On September 4, 2017, seven central government regulators — the PBOC, the Cyberspace Administration of China (CAC), the Ministry of Industry and Information Technology (MIIT), the State Administration for Industry and Commerce (SAIC), the China Banking Regulatory Commission (CBRC), the China Securities Regulatory Commission (CSRC), and the China Insurance Regulatory Commission (CIRC) — jointly issued the Announcement on Preventing Financial Risks from Initial Coin Offerings, which banned initial coin offerings (ICOs) in China.
COP	1	0	0	Jun, 2017			The Superintendencia Financiera (SF) (Financial Superintendency) of Colombia warned in a June 2017 circular that bitcoin is not currency in Colombia and therefore may not be considered legal tender susceptible of cancelling debts.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
CZK	0	0	3			Nov, 2014	Amendments have been made to the Czech Republic's anti-money laundering legislation, making it also applicable to persons providing services related to virtual currencies, i.e. those who buy, sell, store, manage, or mediate the purchase or sale of virtual currencies or provide other services related to such currencies as a business law on 14 November 2016.
GBP	0	1	1		Mar, 2014		For unincorporated businesses, income tax is chargeable to the profits and losses that can be attributed to cryptocurrency transactions. The UK also taxes the earnings of transactions in which a gain is realized after a transaction with cryptocurrencies if an individual user buys and sells coins as an investor. Such gains fall within capital gains tax, and this tax is chargeable to any gain made that involves a cryptocurrency.
HRK	0	0	0				
HUF	0	0	0				
IDR	1	0	0	Jan, 2018			On January 13, 2018, Bank Indonesia (Indonesia's central bank) released a statement that warns against buying, selling, or otherwise trading in virtual currencies.
ILS	0	1	2		Jan, 2018	Feb, 2018	Although virtual currencies are not recognized as actual currency by the Bank of Israel, the Israel Tax Authority has proposed that the use of virtual currencies should be considered as a "means of virtual payment" and subject to taxation.
INR	0	0	0				On April 6, 2018, the RBI issued a notification prohibiting banks, lenders and other regulated financial institutions from "dealing with virtual currencies,"

Laws and Regulations (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
JPY	0	1	3		Dec, 2017	2017 (Month Unknown)	Under the Act on Prevention of Transfer of Criminal Proceeds, cryptocurrency exchange businesses are obligated to check the identities of customers who open accounts, keep transaction records, and notify authorities when a suspicious transaction is recognized. According to the National Tax Agency (NTA), the profit earned by sales of cryptocurrency is, in principle, considered miscellaneous income, rather than capital gains. The NTA compiled questions and answers regarding the tax treatment of cryptocurrency and posted it online on December 1, 2017
KES	0	0	1				
KRW	0	0	3		Jun, 2018	Jul, 2017	Under the Act on Reporting and Using Specified Financial Transaction Information, financial institutions are required to report financial transactions that are suspected, based on reasonable grounds, to be illegal or to involve money laundering July 26, 2017.
MXN	0	0	2			Aug, 2018	Mexico has enacted a law extending the application of its laws regarding money laundering to virtual assets, thereby requiring financial institutions that provide services relating to such assets to report transactions exceeding certain amounts.
PHP	0	0	0				
PKR	2	0	0	Feb, 2018			The Federal Investigation Agency (FIA) has launched operations against the people dealing in the cryptocurrencies.
PLN	0	1	0		Apr, 2018		On April 4, 2018, the Ministry of Finance published guidance on the tax effects of trading in cryptocurrencies.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
RON	0	1	0		Mar, 2018		In March of 2018 the National Agency for Fiscal Administration reportedly declared that income from transactions with cryptocurrencies are taxable.
RUB	0	1	0		Jul, 2018		It is expected that the legislative framework for cryptocurrency regulation will be enacted by July 1, 2018, after which the rules on the taxation of cryptocurrency operations will be introduced.
SAR	1	0	0	Jul, 2018			The Saudi Arabian Monetary Agency (SAMA) has issued a warning on July 4, 2017 against bitcoin because it is not being monitored or supported by any legitimate financial authority.
SEK	0	1	1		Apr, 2015		In 2015 the Swedish Tax Authority published a guideline on how it will view and tax mined bitcoins for the 2014 tax yea.
THB	1	0	0	Feb, 2018			The Bank of Thailand issued a circular on February 12, 2018, asking financial institutions to refrain from doing any business involving cryptocurrencies.
UAH	0	0	0				
VND	2	0	0	Oct, 2017			The State Bank of Vietnam issued a decree on cryptocurrency on October 30, 2017
ZAR	0	1	1		Apr, 2018		On April 6, 2018, the South African Revenue Services (SARS) issued a clarification on the tax status of VCs.

B.5 For Online Publication: Blockchain, Cryptocurrency Storage, and Trading

B.5.1 PoS and PoW

PoW or PoS protocols are the two most popular systems for transaction validation. Both systems do not need a trusted third party. Here are how the two systems work. For example, Bitcoin adopts Proof-of-Work (PoW) consensus mechanism and relies on miners to verify the transactions. Miners compete in solving complex mathematical puzzles, and the first winner becomes the validator for a block. Once the transaction gains approval by over 50% of miners in the network, the transaction will be recorded on the blockchain, and the validator will get block rewards. The design of PoW-based blockchain guarantees decentralization and security with digital democracy, although the efficiency is much lower than relying on a centralized bookkeeper.

In recent years, the Proof-of-Stake (PoS) protocols have become more and more popular. Saleh (2020) conducts the economic analysis of PoS blockchain. Different from PoW, validators lock up some of their coins as a stake, and the vote allocation depends on the number of coins at hand and their holding periods.[1] PoS-based blockchains can process many more transactions per second than PoW-based blockchains. Ethereum, the second-largest blockchain network, plans to switch from PoW to PoS. A growing number of cryptocurrency exchanges have established their blockchain-based on PoS protocol to decentralize crypto-trading while maintaining a high speed.

B.5.2 Options for Crypto-storage

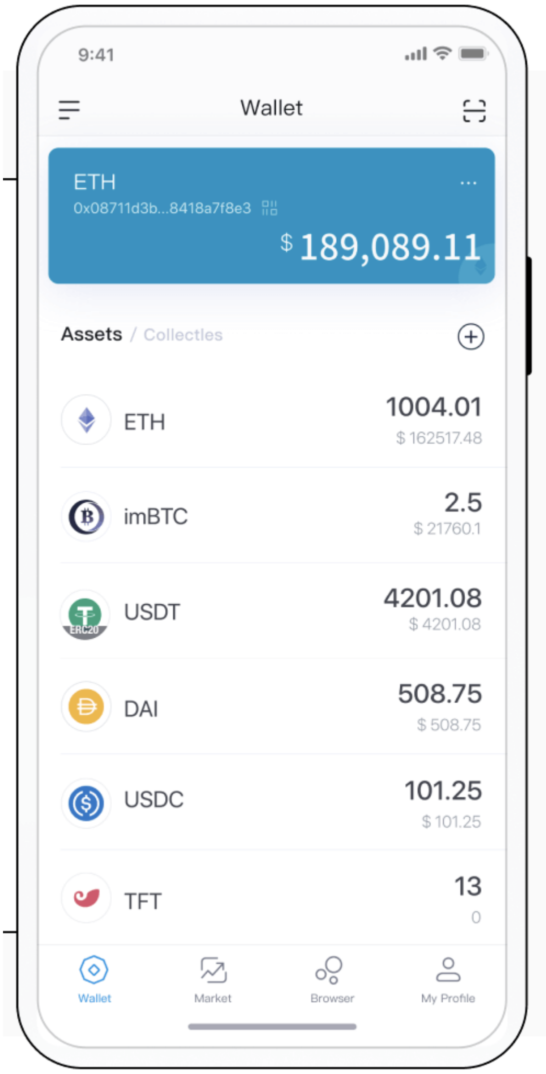
There are multiple ways to store private keys. Nowadays, the most common way to store cryptocurrencies is through cryptocurrency wallets. A cryptocurrency wallet can be a device, a physical machine, a software program, or a third-party service that stores private and public keys. Generally, all wallets belong to two types: centralized wallets and decentralized wallets. Centralized wallets, often known as "hot" wallets, typically store information online in a centralized server. Online storage makes it convenient and easy for investors to trade or send cryptocurrencies. It can also put

[1] Different PoS-based protocol may have different specific rules of consensus, but they all depend on the coins held on stake.

investors at the risks of scam and hack.

Another category of cryptocurrency wallets is decentralized wallets, also known as “cold” wallets. Decentralized wallets typically store investors’ private keys offline. For investors concerned with hack risks, they can use “cold” hardware wallets to save their private keys. Popular decentralized wallets include Imtoken, Bitpie, GeeK Wallet, ColdLar, Trezor, and Ledger. Investors can get rid of the third-party to keep their private keys. Figure B.17 and B.18 are examples of online and offline “cold” wallets. The imKey Pro Hardware Wallet is sold at $99 without any further storage fee. It is as convenient as a normal hard drive. With decentralized wallets, investors can keep cryptocurrencies offline and avoid third-party storage risks.

Figure B.17: Centralized Wallet



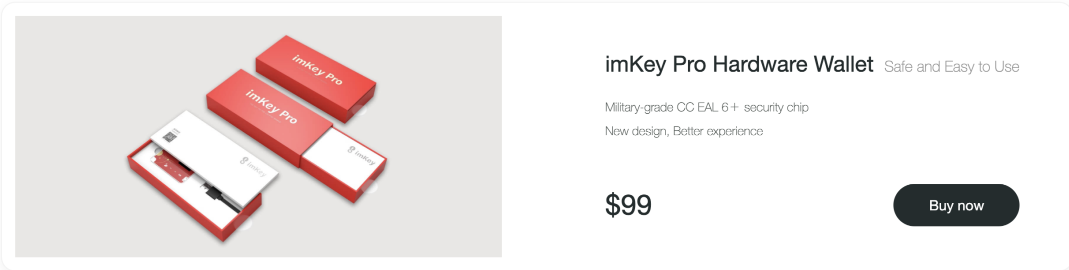
Notes: This figure shows an example of online "hot" cryptocurrency wallet.

B.5.3 Options for Crypto-trading

Investors can trade cryptocurrencies through cryptocurrency exchanges or Over-the-counter (OTC) markets. We can broadly classify cryptocurrency exchanges into centralized and decentralized as well. In this context, decentralization refers to no ownership delegation to the third party for trading. Currently, mainstream cryptocurrency exchanges are mostly centralized exchanges.[2] These exchanges

[2]Large centralized exchanges include Coinbase, Binance, Huobi, Bitfinex, Kraken, etc.

Figure B.18: Decentralized Wallet



Notes: This figure shows ImKey Pro, an example of offline "cold" cryptocurrency wallet.

record all transactions in their centralized database, and investors' private keys are in the custody of the exchanges. Investors can withdraw their cryptocurrencies from the exchange wallets to their personal wallets to minimize scam or hack risks. The centralized exchanges are more and more regulated by national authorities.[3]

If investors do not trust any centralized authorities, they can trade cryptocurrencies through decentralized exchanges. Users directly send or receive Bitcoins with private wallets without interaction with the crypto-exchange. Figure B.19 illustrates the difference between centralized and decentralized exchanges. Decentralized exchanges typically rely on smart contracts to implement transactions; smart contracts record transactions on the public blockchain, instead of the exchanges' database.[4] Decentralized exchanges are slower than centralized exchanges but effectively eliminate the intermediation risk.

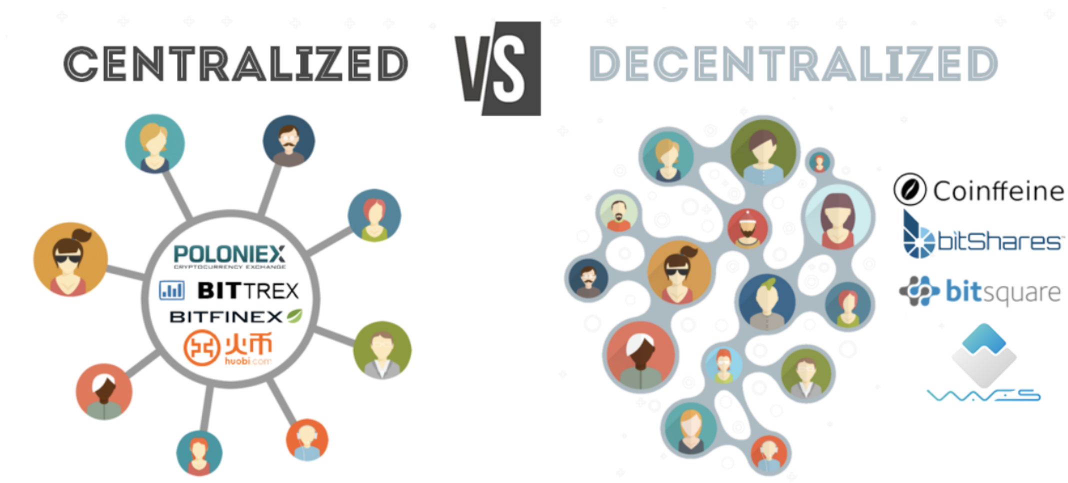
The last option is the OTC platform. OTC platforms differ from the centralized exchanges because the trade happens directly between two parties; they also differ from decentralized exchanges as they typically do not use blockchain technologies. Buyers and sellers can find advertisements that

[3]For example, Coinbase, one of the largest cryptocurrency exchanges, and another 5 exchanges are under US regulations, and 26 cryptocurrency exchanges have got licensed in Japan by 2020.

[4]Pioneers of decentralized exchanges include Binance DEX, Newdex, WhaleEx, IDEX, DDEX, etc. Figure B.20 and B.21 show the interface of Binance DEX and Binance Chain. Binance DEX is the decentralized exchange developed on top of the Binance Chain, which uses a PoS-based consensus mechanism to produce blocks among a series of qualified validators. Binance DEX does all of its matchings on the blockchain to ensure maximum transparency and mitigate front-running chances. Once both parties agree on the price and quantity, sellers will automatically send crypto-assets into buyers' accounts governed by smart contracts. The confirmation is instant, and no need to wait for other blocks. Buyers can dispose of the bought crypto-assets immediately.

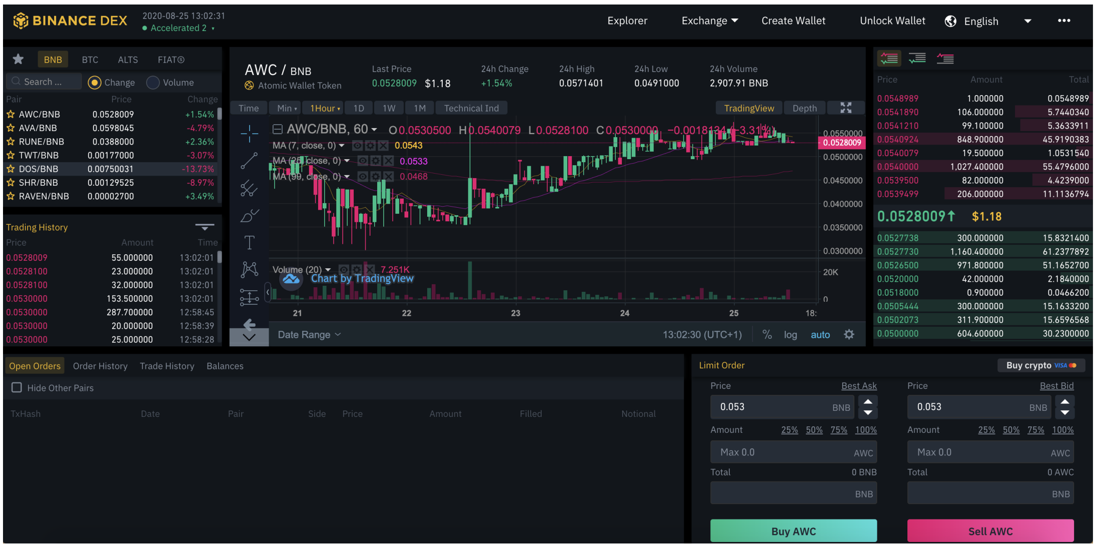
quote price and quantity on the OTC marketplace. Transactions can happen from tokens to tokens (such as BTC to ETH), or fiat currencies to tokens (such as USD to BTC). OTC platforms only provide information and typically do not need any bank account; thus, they are hard to regulate by the government. Some OTC markets specialize in large volume transactions (e.g., Huobi OTC). In contrast, other OTC markets (e.g., Localbitcoin: Figure B.22 show the webpage of Localbitcoins.) post advertisements with much smaller cryptocurrency quantities in different countries.

Figure B.19: Centralized v.s. Decentralized



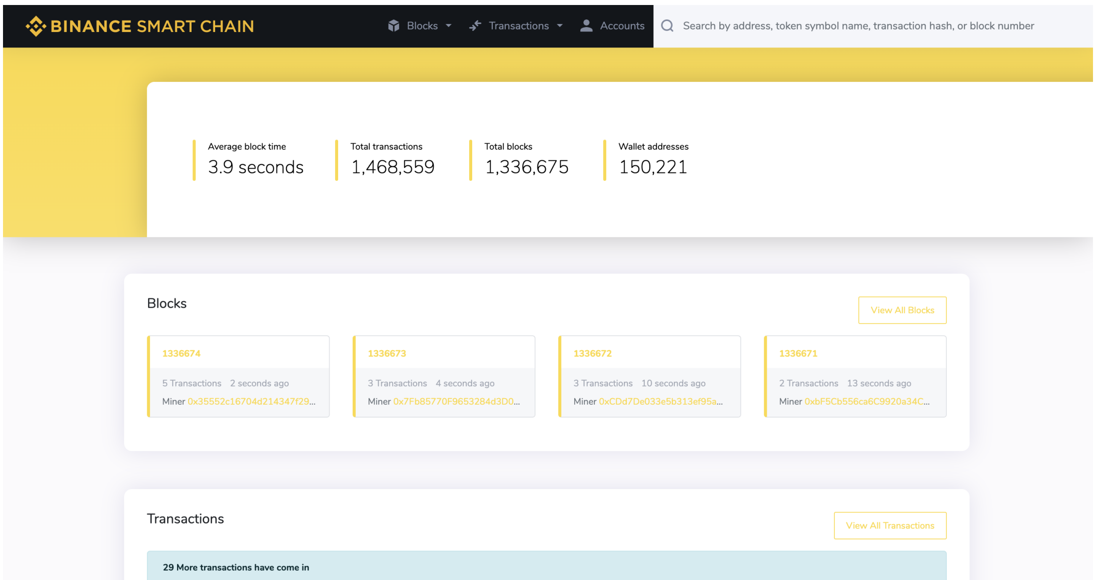
Notes: This figure shows differences between centralized and decentralized exchanges.

Figure B.20: Binance DEX



Notes: This figure shows the interface of Binance DEX.

Figure B.21: Binance Smart Chain



Notes: This figure shows the interface of Binance Chain's block explorer.

Figure B.22: OTC Platform: Localbitcoins

Buy bitcoins online in United Kingdom

Seller	Payment method	Price / BTC	Limits	
goog00 (30+; 100%)	National bank transfer: United Kingdom	5,985.56 GBP	500 - 736 GBP	Buy
camilo19904286 (100+; 100%)	National bank transfer: United Kingdom	5,985.56 GBP	150 - 1,228 GBP	Buy
BitBroker.co.uk.Laura (10 000+; 100%)	National bank transfer: United Kingdom	5,989.65 GBP	150 - 29,006 GBP	Buy
BitBroker.co.uk.Ricky (50 000+; 100%)	National bank transfer: United Kingdom	5,989.66 GBP	150 - 26,267 GBP	Buy
LondonLink (15 000+; 100%)	National bank transfer: United Kingdom	5,989.69 GBP	200 - 60,000 GBP	Buy
Richard-CoinStand.co.uk (3000+; 100%)	National bank transfer: United Kingdom	5,989.69 GBP	150 - 17,702 GBP	Buy

Notes: This figure shows the webpage of Localbitcoins.