# Distrust and Cryptocurrency*

Bo Tang† Yang You‡

January 28, 2021

**Abstract**

This paper uses violations of the law of one price of Bitcoin to uncover sources of demand for cryptocurrency. In line with Hayek, we show that distrust breeds demand. 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. These price responses are stronger in countries where people express more distrust in others.

JEL-Classification: G11, G12, G15.

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

*We are thankful to Andrea Carnelli, Jon Danielsson, Dave Donaldson, Daniel Ferreira, Charles Goodhart, Robin Greenwood, Keyu Jin, Christian Julliard, Dong Lou, Igor Makarov, Robbie Minton, Daniel Paravisini, Kenneth Rogoff, Andrei Shleifer, Liliana Varela, Dimitri Vayanos, Luis Viceira, David Yermack, Kathy Yuan and seminar participants at Chinese University of Hong Kong, Harvard University, London School of Economics, Pantheon, Peking University, and University of Hong Kong for helpful comments and suggestions.

†London School of Economics, Department of Finance; b.tang3@lse.ac.uk.

‡Harvard University, Department of Economics; yangyou@g.harvard.edu.

*Since the function of government in issuing money is no longer one of merely certifying the weight and fineness of a certain piece of metal, but involves a deliberate determination of the quantity of money to be issued, governments have become wholly inadequate for the task and, it can be said without qualifications, have incessantly and everywhere abused their trust to defraud the people ... We have no choice but to replace the governmental currency monopoly and national currency systems.*

— F.A. Hayek. *The Denationalisation of Money*

# 1 Introduction

In the famous book *The Denationalization of Money*, Hayek (1978) argues that distrust in government and central banks justifies the demand for denationalized private money. 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? We use the trust measure in the Global Preference Survey, which asked respondents whether they assume that other people only have the best intentions.[1] Our paper offers empirical support for the distrust argument.

To identify sources of Bitcoin demand, we study the prices of Bitcoin expressed in different currencies. 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. The 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, 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 drive local Bitcoin prices higher relative to the international market.

Then, we test the model predictions in Bitcoin trading data from 2015 to 2020. To evaluate Hayek's argument, 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 percent 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 the 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 give content to the sources of frictions empirically 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. Cryptocurrency regulations appear to be 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

[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 Siamnese-twin stocks in different markets around the world with identical claims of cash flow but different

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 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 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 provides a theoretical framework of trust in portfolio choice and makes testable predictions. Section 4 brings empirical predictions to the Bitcoin trading data, investigates the determinants of price deviations, and highlights the importance of distrust on Bitcoin demand. Section 5 investigates the limits of arbitrage in crypto-trading. Section 6 explores the micro foundations in trust, validates the model assumption, and discusses implications in investment strategies. Section 7 concludes.

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 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.

# 2 Motivating Facts

## 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 sample, Japan (-0.51873) is the lowest trust country, and China (0.55281) is the highest trust country. Figure 1 Panel A shows the correlation between the trust level and log numbers of Bitcoins traded in the country's currency in 2019. Table 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 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

[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.

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

[8] Section 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.

residual trading volume.[10]

## 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 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 A.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

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

[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.

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 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%.

# 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 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.

## 3.1 Model Setup

### 3.1.1 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 $\sigma_b^2$.

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

[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.

can quickly detect if any cheating happens. Thus, in equilibrium, no cheating happens to the risk-free asset.

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 $\mu_G$ and $\sigma_G$ 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 6.3.

### 3.1.2 Investors

We consider a representative cryptocurrency investor who is myopic with constant relative risk aversion (CRRA) $\gamma$. The investor optimizes the portfolio choice from all three assets by maximizing the expected utility: $\pi_G$ of wealth invested in cryptocurrency, $\pi_L$ 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 $\pi_G$ is inelastic to the price deviation.[15]

[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.

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

### 3.1.3 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.

$\kappa$ is the price elasticity relative to the excess demand.[17] $\kappa$ is the parameter that reflects the limits of arbitrage discussed in the Section 5. When market friction increases, a higher $\kappa$ 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.

## 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]

[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.1 for math derivation.

**Proposition 1 (two-asset case)**: Portfolio weight $\pi_L$ 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 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 $\pi_G$ with the first-order approximation with respect to $p$.

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

[19] See Appendix B.2 for math derivation.

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

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

**Comments**: The first term $\Pi_G^b$ 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 $\sigma_b^2$, the uncertainty in cheating loss.

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 $\chi$ can be rewritten as $\frac{1}{\gamma}\frac{\rho}{1-\rho^2}\frac{1}{\sigma_L\sigma_G}$. Then, we can rewrite $\eta = \frac{\rho}{\sigma_L\sigma_G}\Pi_t^L$. $\Pi_t^L$, the demand for the local risky asset with perfect trust, must be positive as domestic investments are assets with positive net supply.

## 3.3 Empirical Predictions

Empirically, it is hard to distinguish between the average loss from cheating $E(B)$ and perceived trust risk $\sigma_b^2$. 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:

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

$\kappa$ 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. $\chi$ is proportion-

ate to risk appetite $\frac{1}{\gamma}$. $\Pi_G$ 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 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 $\kappa$ 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* ($\chi$)

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

# 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 ($\kappa$), and changes in risk appetites ($\gamma$); we study

their predictability in the domestic Bitcoin price deviation and document the significant role of trust.

## 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.

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.

## 4.2 Institutional Failures and Trust

We 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.[23]

[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.

[22] Canadian stocks are from Compustat North America.

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

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

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

Table A.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 reports the results of the following regression:

$$Deviation_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t} \tag{1}$$

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.[24]

Table 4 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

[24]Table A.4 reports robustness check results when controlling Bitcoin returns and currency returns.

keywords.[25,26]

Before moving forward, we manually check the real events behind the Google search spikes. Table A.3 gives some examples of institutional disruptions that correspond to Google search spikes, including military conflicts, sovereign credit downgrades, monetary system crisis, political and corruption scandals. Appendix C 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.[27]

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 5 Columns (2) - (4) report the regression results in Eq.(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:

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

[25]In Table A.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.

[26]Table A.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.

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

The coefficient $\beta_2$, 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 A.7 presents the results for the other three keywords ("Crisis," "Instability," and "Scandal") and shows a similar pattern.[28]

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 scores.[29] Table A.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 5 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.

## 4.3 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.

[28] 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).

[29] 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.

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

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.[30] Table 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 6 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 6 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.

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

[30] 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 A.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 A.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).

We add the interaction term with distrust in Column (5). The coefficient $\beta_2$ is 0.11 ($t$ = 2.20), consistent with Prediction 3.

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

## 4.4 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 7 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).[31]

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 8 Columns (1) - (4) report the results:

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

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

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

## 4.5 Distrust Loss Elasticity

We estimate the distrust loss elasticity $\chi$ as in Prediction 5: the cryptocurrency demand response to a unit change in the cheating loss $Bp$. We identify $\chi$ 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 $\chi$ 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].[32] $\chi$ represents the cryptocurrency demand response to one s.d. 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 9 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

[32] 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.

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. $\chi$ estimates, ranging from 0.33 to 0.62, are positive, thus broadly consistent with Prediction 5.

# 5 Limits of Arbitrage

Our identification of Bitcoin demand entirely relies on the law of one price violations in Bitcoin trading. Investors must face limits of arbitrage, at least in the short run, so that transitory price deviations can exist in the data. Moreover, 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). This section examines different types of frictions in the Bitcoin arbitrage and evaluates how these frictions explain the cross-country variation in return asychronization.

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. It is often argued in the literature that capital controls (Step 6) are the primary reason for the price deviations

across countries in the literature.[33] Our results imply that capital controls can only explain 13% of cross-country variation in return asynchronization. The frictions in trading between cryptocurrency and fiat money play a more critical role in the short horizon. In the following sections, we first investigate capital controls — the conventional explanation — then examine crypto-fiat liquidity, market segmentation, Bitcoin mining, and legal perspectives.

## 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 A.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 (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.[34]

Table A.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

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

[34] 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.

not find that retail transfer costs correlate with the return asynchronization, as shown in Columns (3) - (6). Our findings confirm that capital controls matter, but they are still not sufficient to explain such considerable variation in asynchronization.

## 5.2 Insufficient Liquidity

But why do we 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.[35] 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 A.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%.

## 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.[36] 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

[35] 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.

[36] See Appendix E.3 for the details about OTC platforms.

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.[37,38] 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 A.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 A.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% 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 A.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

[37] https://www.binance.com/en/fee/depositFee
[38] https://help.coinbase.com/en/coinbase/trading-and-funding/pricing-and-fees/fees

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.

## 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 A.8 shows the rise of return asynchronization after the ban became effective in November.[39] 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 D 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 ban or announce policies against cryptocurrencies.[40]

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

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

[40] 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.

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.[41]

Table A.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 A.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.[42]

## 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.[43] 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

[41] 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.

[42] 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/.

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

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.[44]

# 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, and further discuss the connection between the Bitcoin price deviations with FX markets. Finally, we explore implications in investment strategies.

## 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.[45] 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

[44] 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.

[45] Appendix E.1 discusses how PoW and PoS protocols validate transactions.

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.[46] 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.[47] 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.[48] At that stage, users can store, spend, and trade crypto-assets without any intervention by third parties.

## 6.2 Economic Foundations of Distrust

Where does trust come from? 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.[49] 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",

[46] 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.

[47] Appendix E.2 thoroughly discusses the approaches for crypto-storage to balance security and convenience.

[48] Appendix E.3 discusses common approaches for crypto-trading.

[49] 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 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 A.10 and Table A.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 A.11 and Table A.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 A.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.

## 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.[50]

We validate stocks and cryptocurrencies co-movement, which is $\rho > 0$.[51] In Table A.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.

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 A.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.

## 6.4 Exchange Rates and CIP Deviations

The exchange rate is an essential variable for the price deviation construction. We first evaluate whether exchange rate changes affect the price deviation. Figure A.13 plots coefficients of uni-variate 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

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

[51] 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.

is no. We add currency exchange rate returns and one-week lagged returns to the main specifications in Table A.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 A.13, exchange rate returns do positively predict the price deviations, but orthogonal to factors we identify in Section 4.

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 A.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.

## 6.5 Investment Implications

Given the limits of arbitrage, investors can design trading strategies without moving fiat currency and Bitcoin across the border based on the variables discussed in Section 4. Investors can buy Bitcoins when price deviation dips in the local country and sell the same quantity of Bitcoins on the US crypto-exchange, then reverse the process when the local Bitcoin price rises. This section ranks the variables based on their explanatory power in price deviations and argues that factors out-perform in countries with higher levels of distrust.

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.[52] 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.[53] Table A.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:

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

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 A.18 Columns (2)-(4) show that factors generally out-perform in medium-trust and low-trust countries compared to high-trust countries.[54] 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 A.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.

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

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

[54] 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.

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:

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

Figure A.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%.[55] The slope of the fitted line is -13.69% ($t$ = -1.97). The conclusion also holds if we only focus on institutional failures. Figure A.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).[56] These factors are better predictors in countries with lower trust levels.

[55]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.

[56]We also conduct parallel analysis for each factor by country in Figure A.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.

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

# References


Abadi, Joseph, and Markus Brunnermeier, 2018, Blockchain economics, Technical report, National Bureau of Economic Research.

Auer, Raphael, 2019, Beyond the doomsday economics of'proof-of-work'in cryptocurrencies .

Auer, Raphael, and Rainer Böhme, 2020, The technology of retail central bank digital currency, *BIS Quarterly Review, March* .

Auer, Raphael, and Stijn Claessens, 2018, Regulating cryptocurrencies: assessing market reactions, *BIS Quarterly Review September* .

Auer, Raphael, Giulio Cornelli, Jon Frost, et al., 2020, Rise of the central bank digital currencies: drivers, approaches and technologies, Technical report, Bank for International Settlements.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, and Catherine Casamatta, 2019, The blockchain folk theorem, *The Review of Financial Studies* 32, 1662–1715.

Budish, Eric, 2018, The economic limits of bitcoin and the blockchain, Technical report, National Bureau of Economic Research.

Caporale, Guglielmo Maria, and Woo-Young Kang, 2020, Cross-country co-movement between bitcoin exchanges: A cultural analysis .

Catalini, Christian, and Joshua S Gans, 2020, Some simple economics of the blockchain, *Communications of the ACM* 63, 80–90.

Choi, Kyoung Jin, Alfred Lehar, and Ryan Stauffer, 2018, Bitcoin microstructure and the kimchi premium, *Available at SSRN 3189051* .

Cong, Lin William, and Zhiguo He, 2019, Blockchain disruption and smart contracts, *The Review of Financial Studies* 32, 1754–1797.

Cong, Lin William, Xi Li, Ke Tang, and Yang Yang, 2020, Crypto wash trading, *Available at SSRN 3530220* .

Cong, Lin William, Ye Li, and Neng Wang, 2019, Tokenomics: Dynamic adoption and valuation, *Becker Friedman Institute for Research in Economics Working Paper* 2018–15.

Danielsson, Jon, 2019, Cryptocurrencies: Policy, economics and fairness, *Systemic Risk Centre Discussion Paper* 86, 2018.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990, Noise trader risk in financial markets, *Journal of political Economy* 98, 703–738.

Dorn, Daniel, and Martin Weber, 2017, Losing trust in money doctors, *Available at SSRN 2705435* .

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018, Deviations from covered interest rate parity, *The Journal of Finance* 73, 915–957.

Easley, David, Maureen O'Hara, and Soumya Basu, 2019, From mining to markets: The evolution of bitcoin transaction fees, *Journal of Financial Economics* 134, 91–109.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, 2018, Global evidence on economic preferences, *The Quarterly Journal of Economics* 133, 1645–1692.

Fernández, Andrés, Michael W Klein, Alessandro Rebucci, Martin Schindler, and Martin Uribe, 2016, Capital control measures: A new dataset, *IMF Economic Review* 64, 548–574.

Ferreira, Daniel, Jin Li, and Radoslawa Nikolowa, 2019, Corporate capture of blockchain governance, *Available at SSRN 3320437* .

Foley, Sean, Jonathan R Karlsen, and Tālis J Putniņš, 2019, Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?, *The Review of Financial Studies* 32, 1798–1853.

Froot, Kenneth A, and Emil M Dabora, 1999, How are stock prices affected by the location of trade?, *Journal of financial economics* 53, 189–216.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer, 2020, Trust and insurance contracts, Technical report, National Bureau of Economic Research.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Money doctors, *The Journal of Finance* 70, 91–114.

Griffin, John M, and Amin Shams, 2019, Is bitcoin really un-tethered?, *Available at SSRN 3195066* .

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of financial Economics* 66, 361–407.

Gromb, Denis, and Dimitri Vayanos, 2018, The dynamics of financially constrained arbitrage, *The Journal of Finance* 73, 1713–1750.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2006, Does culture affect economic outcomes?, *Journal of Economic Perspectives* 20, 23–48.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *the Journal of Finance* 63, 2557–2600.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2013, The determinants of attitudes toward strategic default on mortgages, *The Journal of Finance* 68, 1473–1515.

Gurun, Umit G, Noah Stoffman, and Scott E Yonker, 2018, Trust busting: The effect of fraud on investor behavior, *The Review of Financial Studies* 31, 1341–1376.

Harvey, Campbell R, 2016, Cryptofinance, *Available at SSRN 2438299* .

Hautsch, Nikolaus, Christoph Scheuch, and Stefan Voigt, 2018, Limits to arbitrage in markets with stochastic settlement latency, *arXiv preprint arXiv:1812.00595* .

Hayek, Friedrich, 1978, *Denationalisation of Money: The Argument Refined* (Institute of Economic Affairs).

Kostovetsky, Leonard, 2016, Whom do you trust?: Investor-advisor relationships and mutual fund flows, *The Review of Financial Studies* 29, 898–936.

Lamont, Owen A, and Richard H Thaler, 2003, Anomalies: The law of one price in financial markets, *Journal of Economic Perspectives* 17, 191–202.

Liu, Yukun, and Aleh Tsyvinski, 2018, Risks and returns of cryptocurrency, Technical report, National Bureau of Economic Research.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu, 2019, Common risk factors in cryptocurrency, Technical report, National Bureau of Economic Research.

Makarov, Igor, and Antoinette Schoar, 2019, Price discovery in cryptocurrency markets, in *AEA Papers and Proceedings*, volume 109, 97–99.

Makarov, Igor, and Antoinette Schoar, 2020, Trading and arbitrage in cryptocurrency markets, *Journal of Financial Economics* 135, 293–319.

Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2002, Limited arbitrage in equity markets, *The Journal of Finance* 57, 551–584.

Rosenthal, Leonard, and Colin Young, 1990, The seemingly anomalous price behavior of royal dutch/shell and unilever nv/plc, *Journal of Financial Economics* 26, 123–141.

Saleh, Fahad, 2020, Blockchain without waste: Proof-of-stake, *Available at SSRN 3183935* .

Sapienza, Paola, and Luigi Zingales, 2012, A trust crisis, *International Review of Finance* 12, 123–131.

Schilling, Linda, and Harald Uhlig, 2019, Some simple bitcoin economics, *Journal of Monetary Economics* 106, 16–26.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *The Journal of finance* 52, 35–55.

Sockin, Michael, and Wei Xiong, 2018, A model of cryptocurrencies, *Unpublished manuscript, Princeton University* .

Yermack, David, 2015, Is bitcoin a real currency? an economic appraisal, in *Handbook of digital currency*, 31–43 (Elsevier).

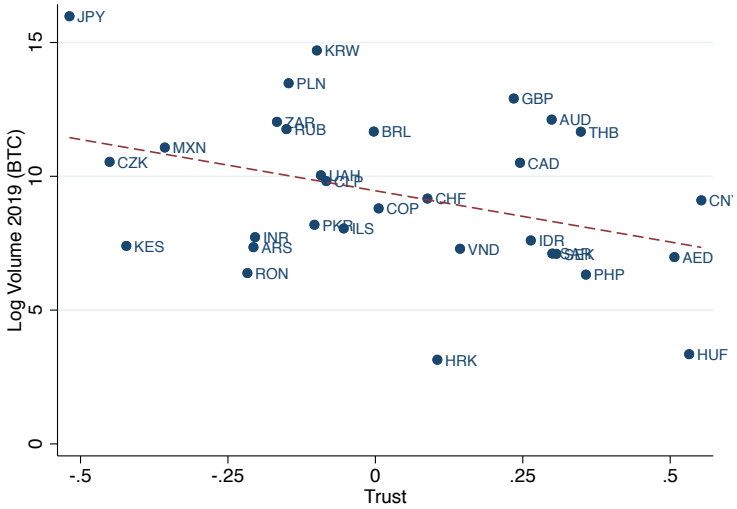
You, Yang, and Kenneth S Rogoff, 2020, Redeemable platform currencies, *National Bureau of Economic Research* .

Yu, Yang Gloria, and Jinyuan Zhang, 2018, Flight to bitcoin, *Jinyuan, Flight to Bitcoin (November 5, 2018)* .

Zak, Paul J, and Stephen Knack, 2001, Trust and growth, *The economic journal* 111, 295–321.

# Figures and Tables

Figure 1: Bitcoin Trading Volume and Trust Level



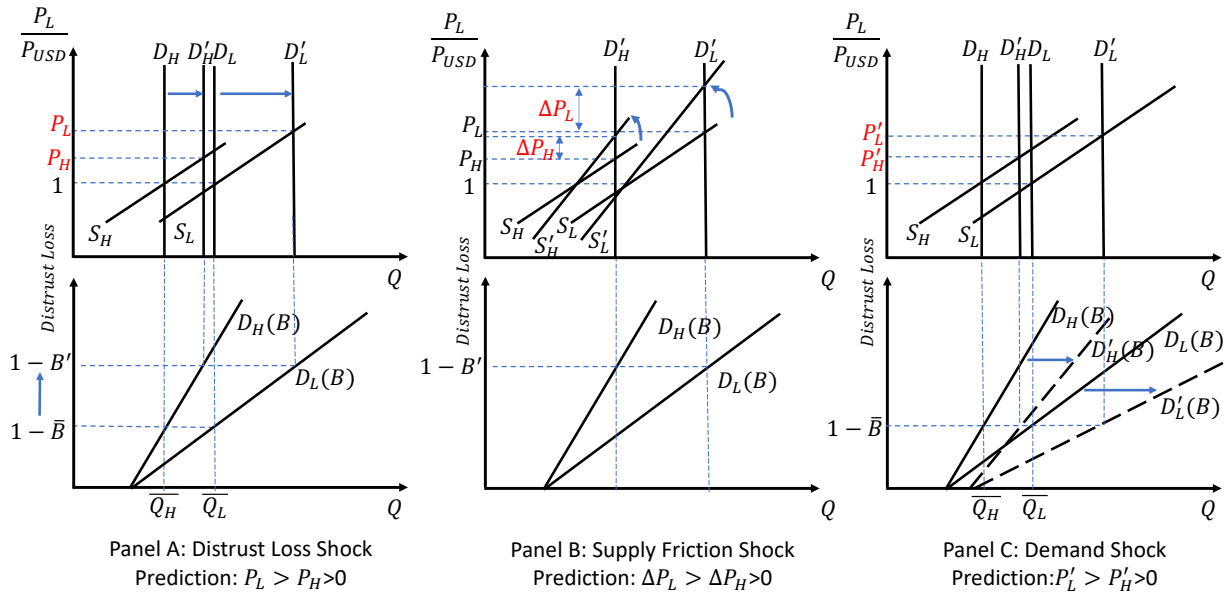

Panel A: Raw Volume


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: 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.

Table 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: 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 3: 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 4: 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 5: 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 6: 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 7: 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 8: 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 9: Distrust Loss Elasticity Estimation

| | (1) Conflict | (2) Crisis | (3) Instability | (4) Scandal |
|---|---|---|---|---|
| Elasticity $\chi$ | 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 |

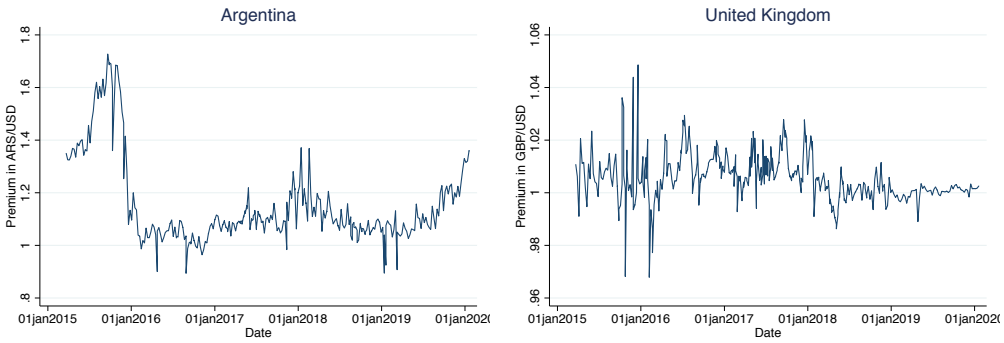
*Notes*: This table reports distrust loss elasticity $\chi$ estimated from the following quasi-triple difference-in-difference specification:

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

$GT_{c,t}$ 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

# A Internet Appendix: Figures and Tables

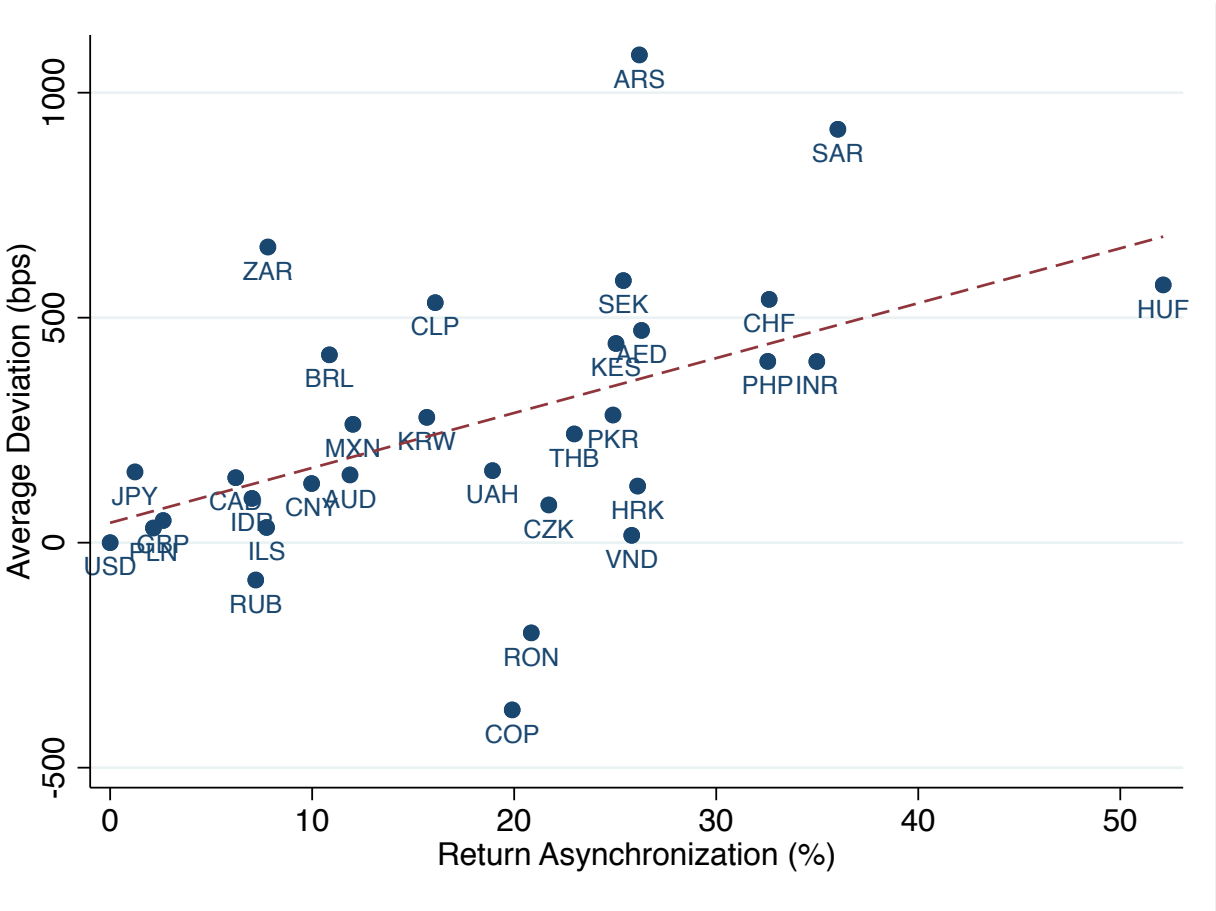
Figure A.1: Price Deviation - Argentina and United Kingdom




*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 A.2: Return Asynchronization and Average Deviation

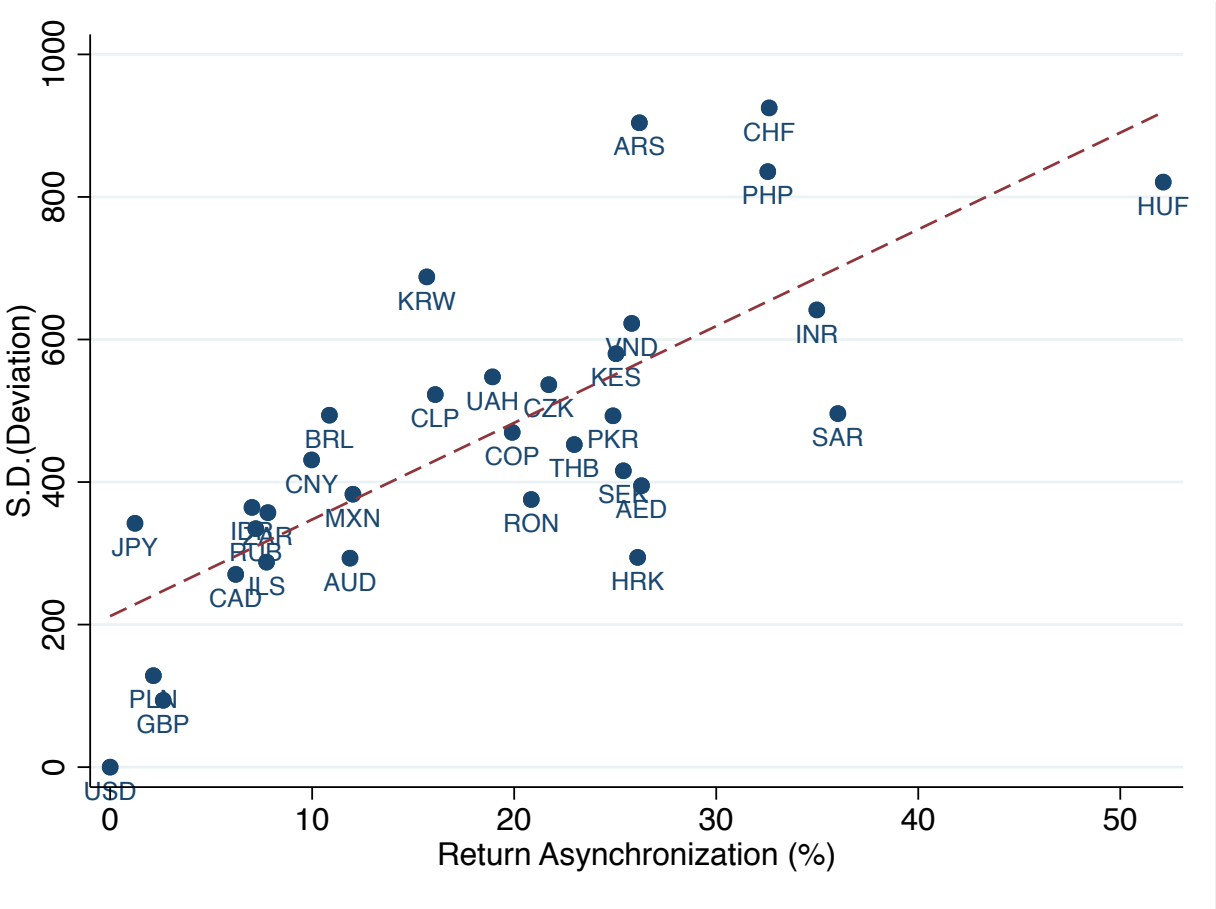



*Notes*: This figure shows the relationship between the average return asynchronization and the average price deviation by currency.

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

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

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

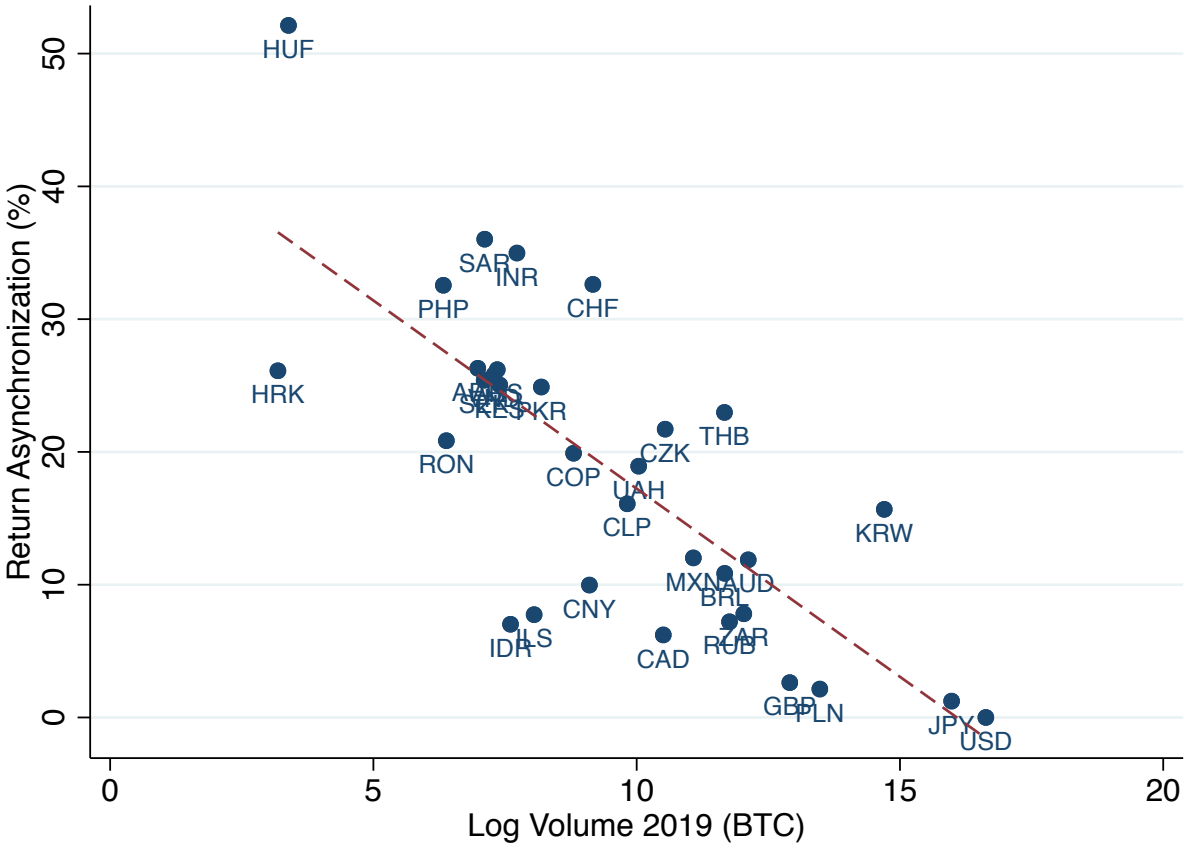



*Notes*: This figure shows the positive relationship between the average return asynchronization and the standard deviation of price deviations by currency.

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

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

Figure A.4: Return Asynchronization and Liquidity

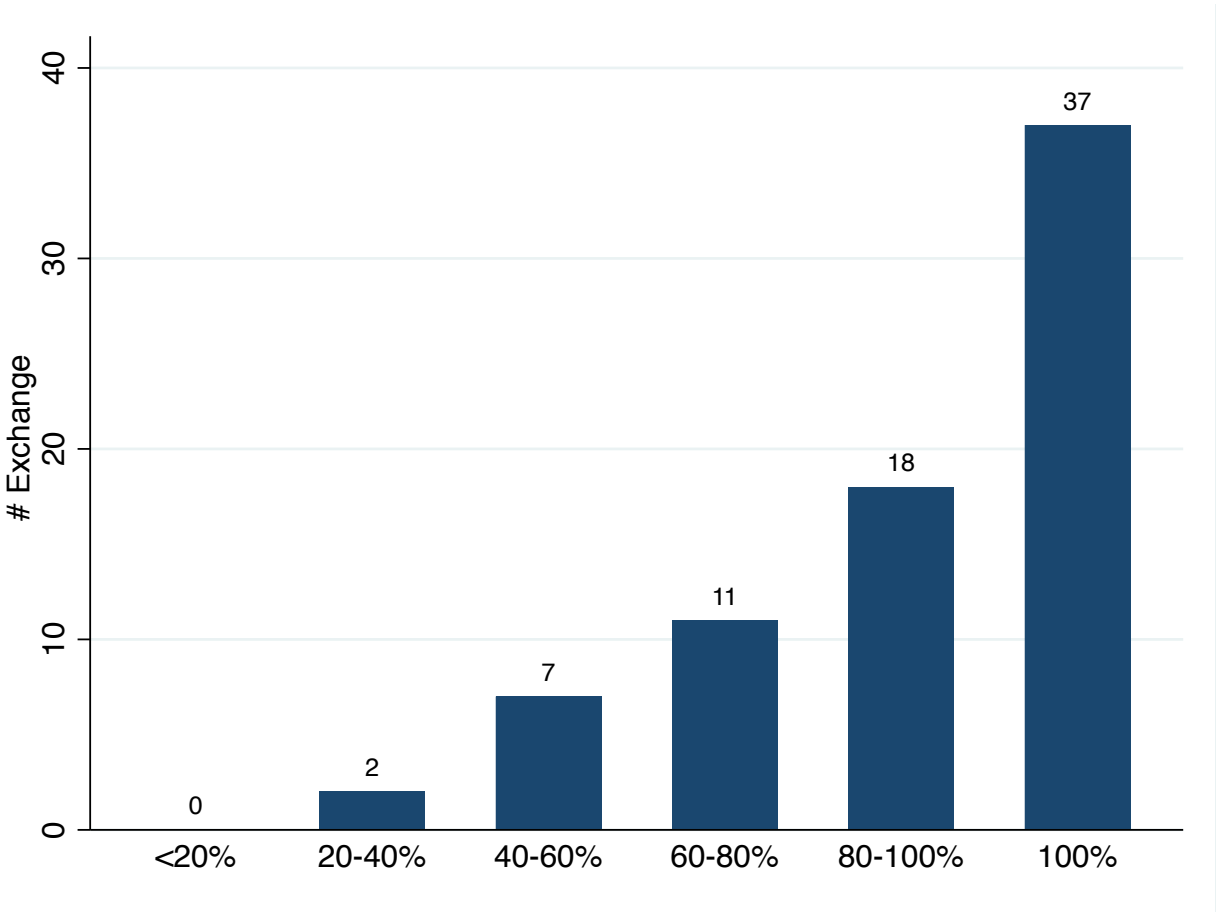



*Notes*: This figure plots the average return asynchronization and log trading volume in 2019.

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

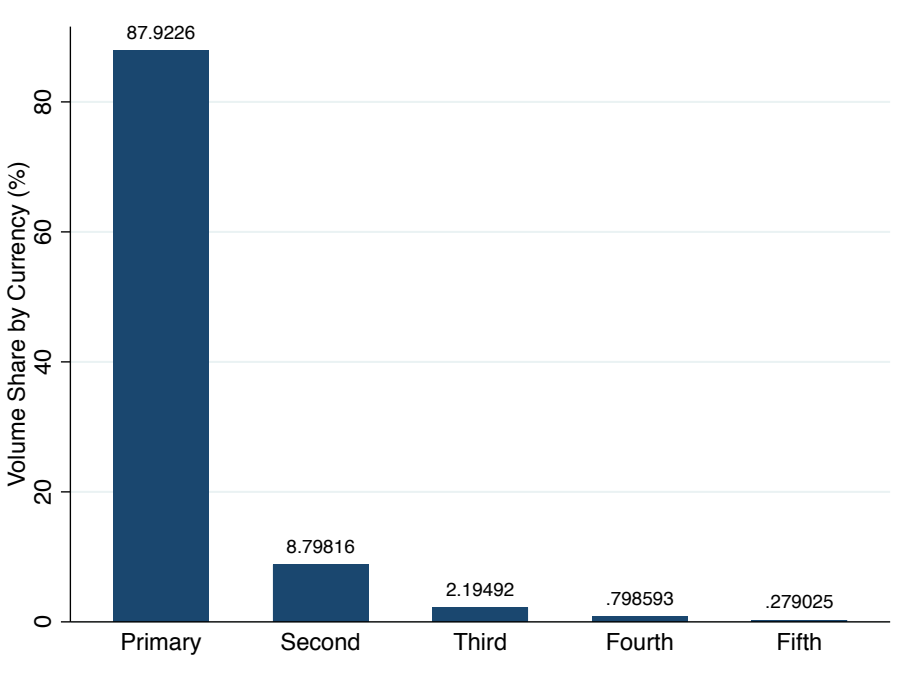
where $\overline{Asyn_c}$ is the average return asynchronization of country $c$, and $Log\_Vol_c$ is the log number of Bitcoins traded in 2019.

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



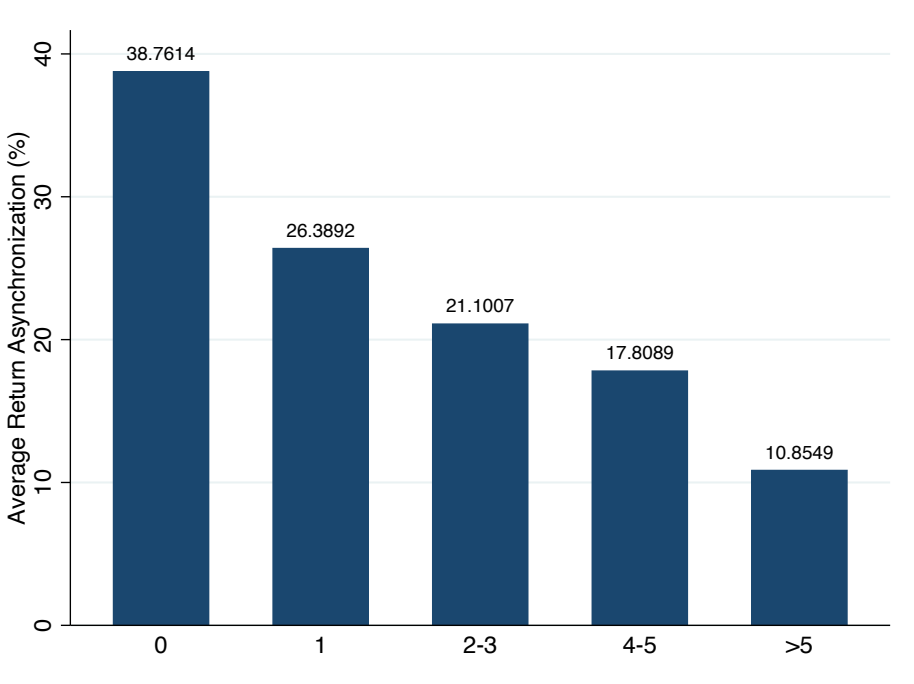

*Notes*: This figure plots the number of exchanges sorted into six categories by the primary trading pair's volume share. 37 out of 75 exchanges have only one fiat currency actively traded. The two "20-40%" exchanges are peer-to-peer listing platform (trading happens outside the exchange): Localbitcoins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

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



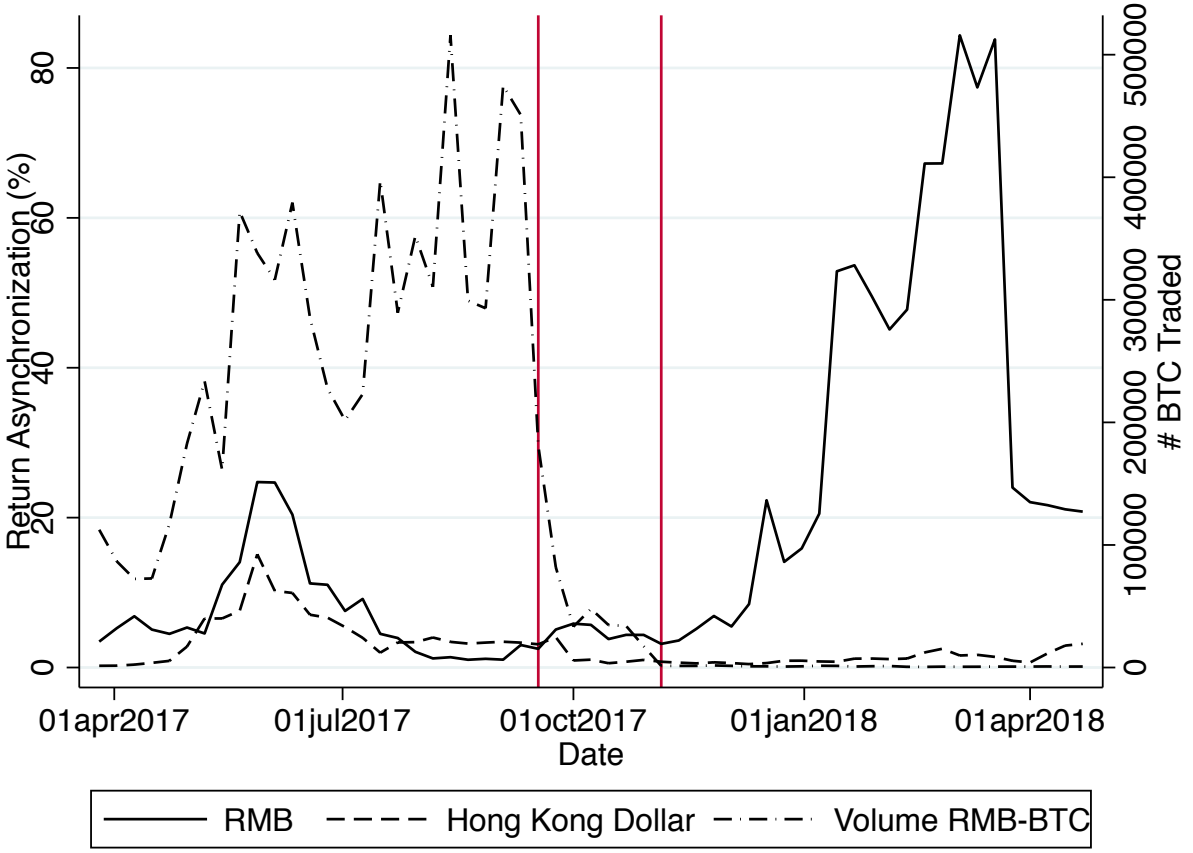

*Notes*: This figure plots the average volume share of the top 5 most active traded fiat currencies (with Bitcoin). The primary trading pair accounts for 87.9% of the total trading volume. The number sharply decreases to 8.80% for the second, 2.19% for the third, 0.80% for the fourth, and the 0.28% for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

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



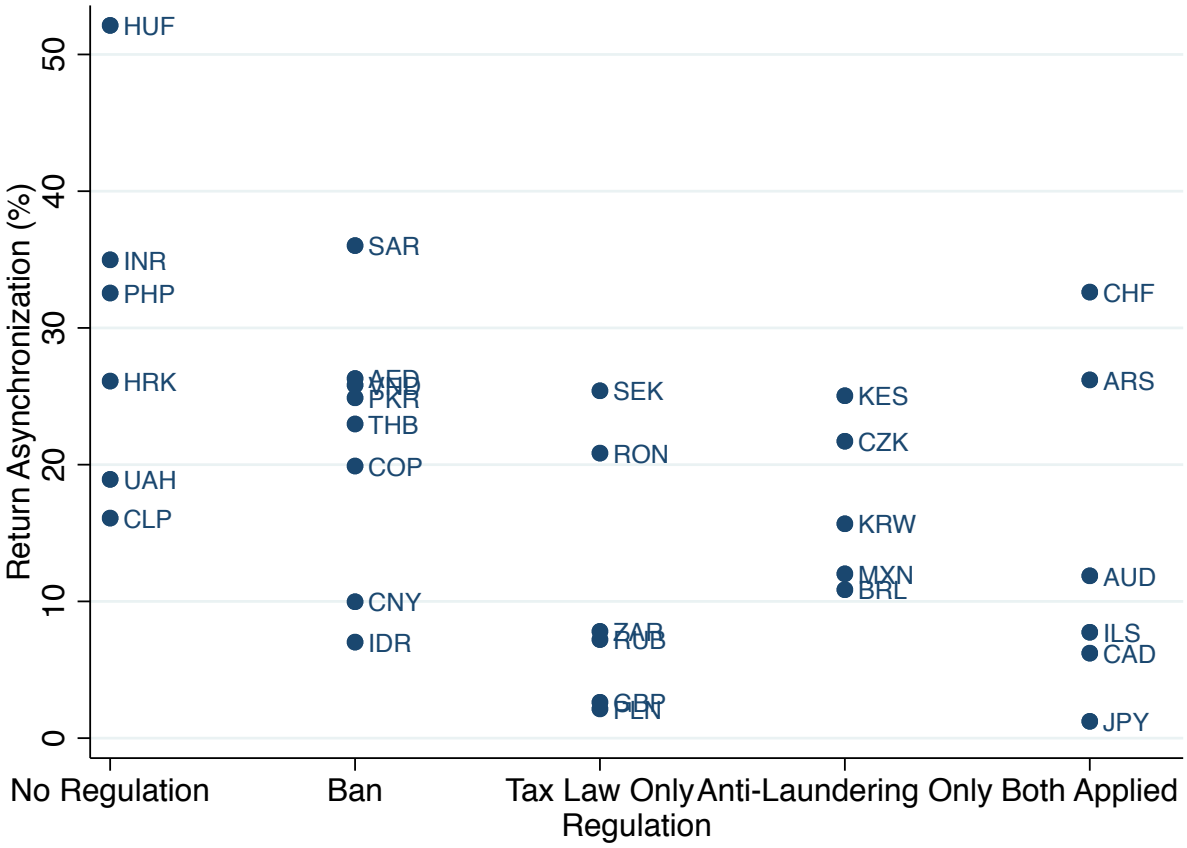

*Notes*: This figure plots the average return asynchronization against the number of exchanges with fiat trading pair by currency. For the 8 currencies with no top 100 exchanges covering their fiat currency, the average return asynchronization is 38.76%. The number decreases to 26.39% for the 7 currencies 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 A.8: China Ban - Friction



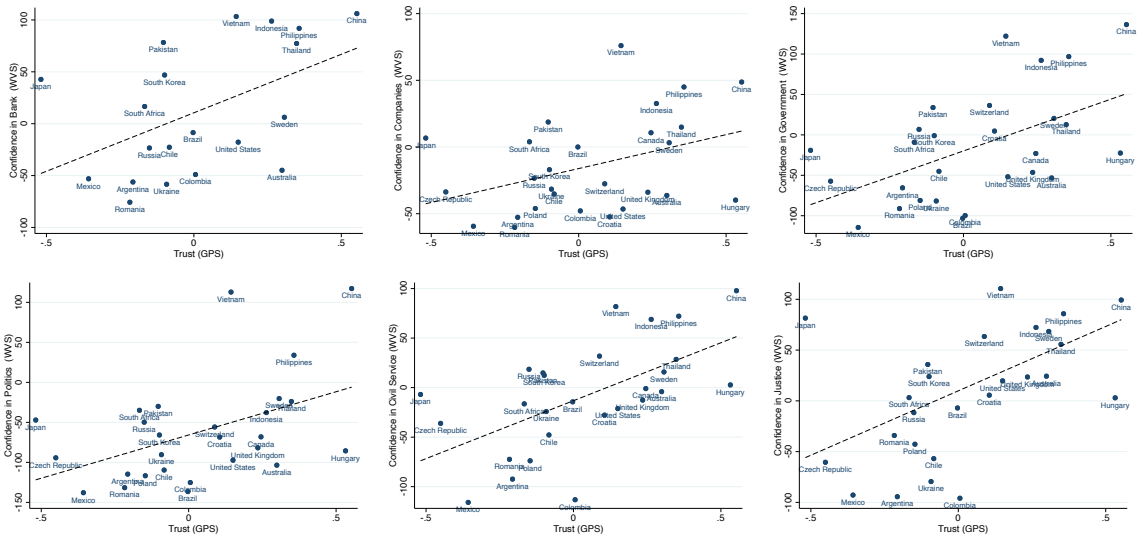

*Notes*: In September 2017, China started its plan to shut down cryptocurrency exchanges in the country. All cryptocurrency exchanges in Beijing and Shanghai were ordered to submit plans for winding down their operations by September $20^{th}$, 2017. Leading crypto-exchanges started to stop trading at 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 A.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."

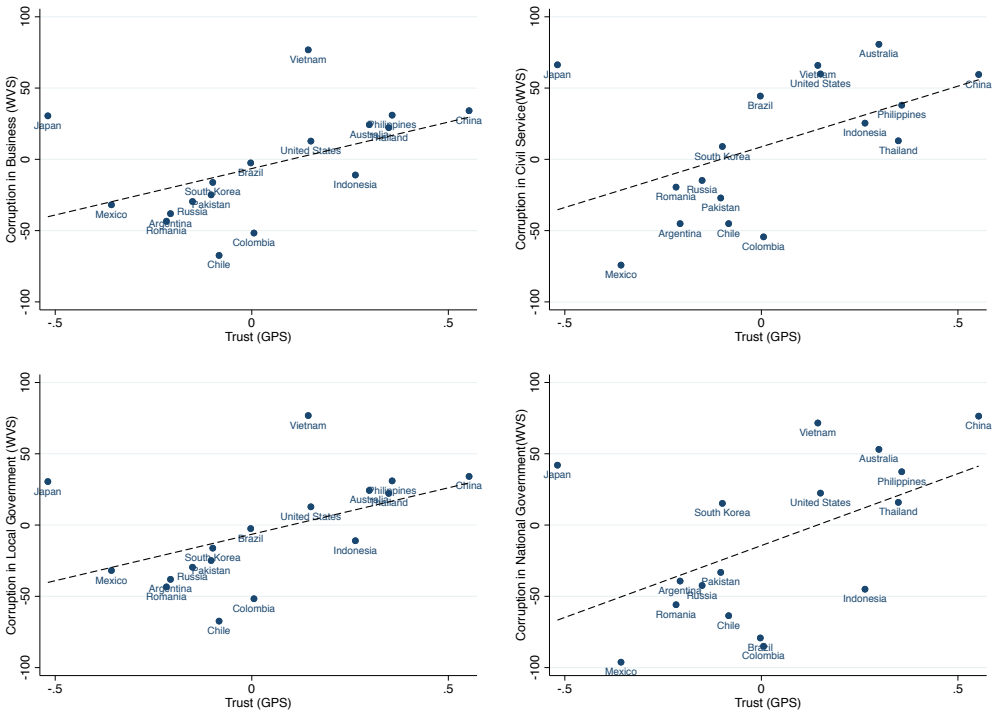
Figure A.10: Trust and Confidence in Institutions




*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.

$$Confidence_c^{WVS} = Trust_c^{GPS} + \gamma\epsilon_c$$

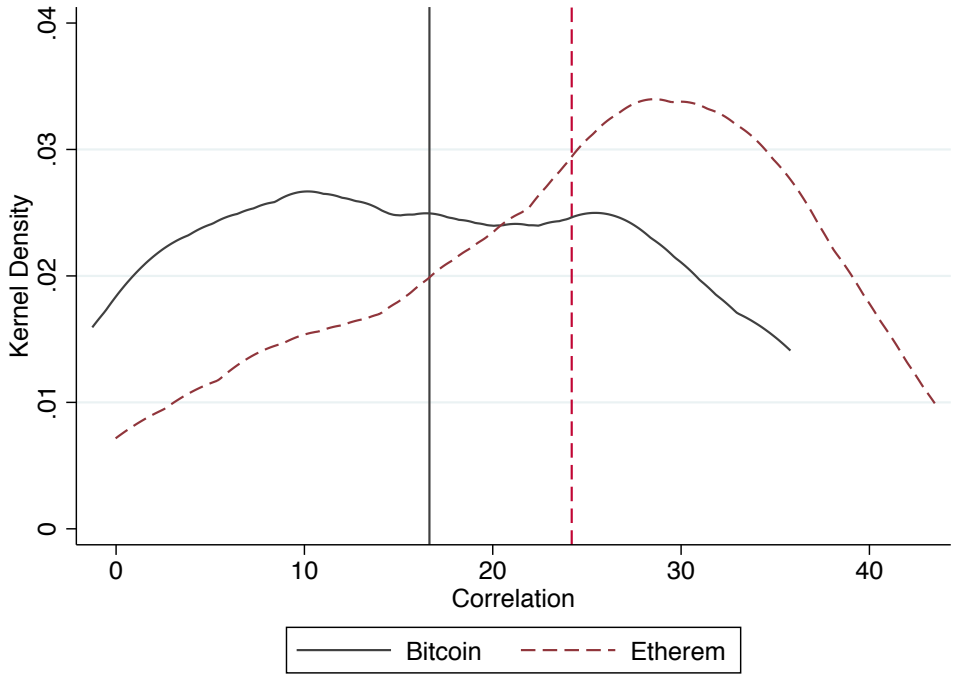
Figure A.11: Perceived Corruption and Trust




*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.

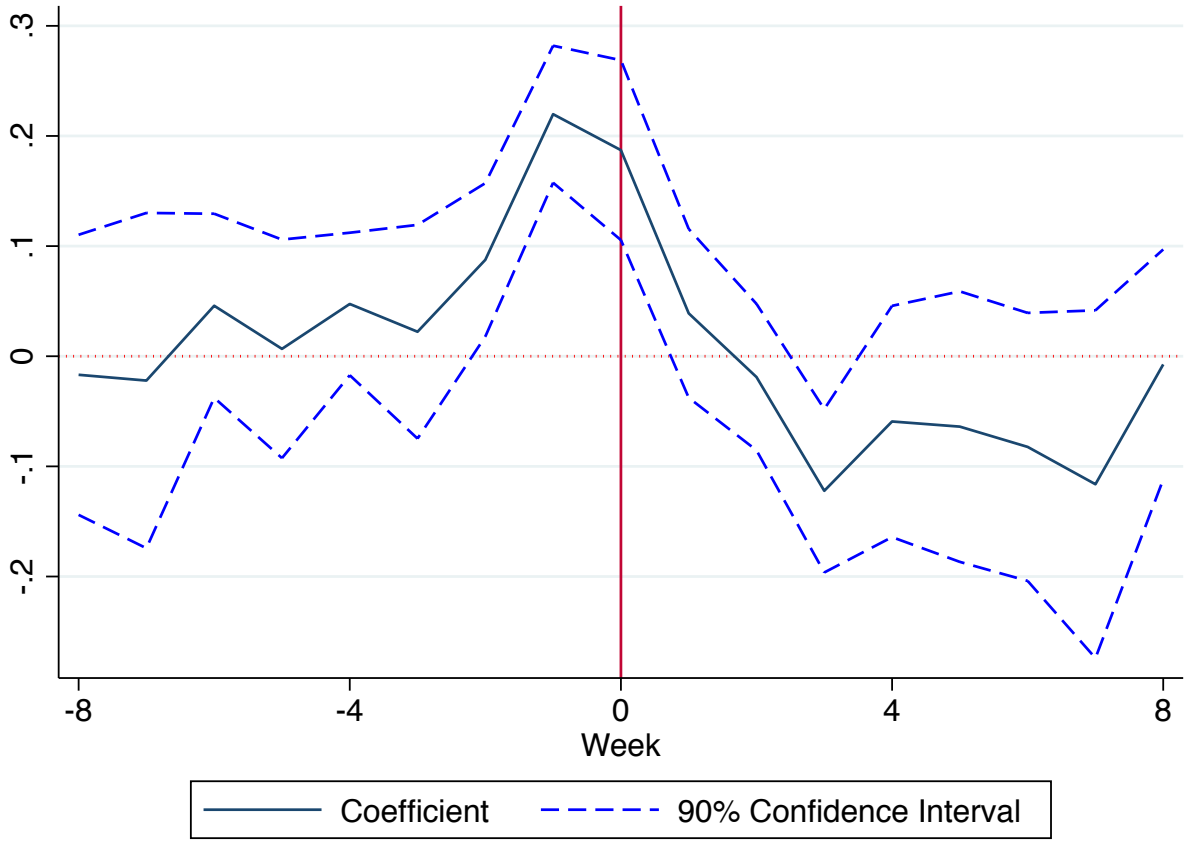
$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Figure A.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.

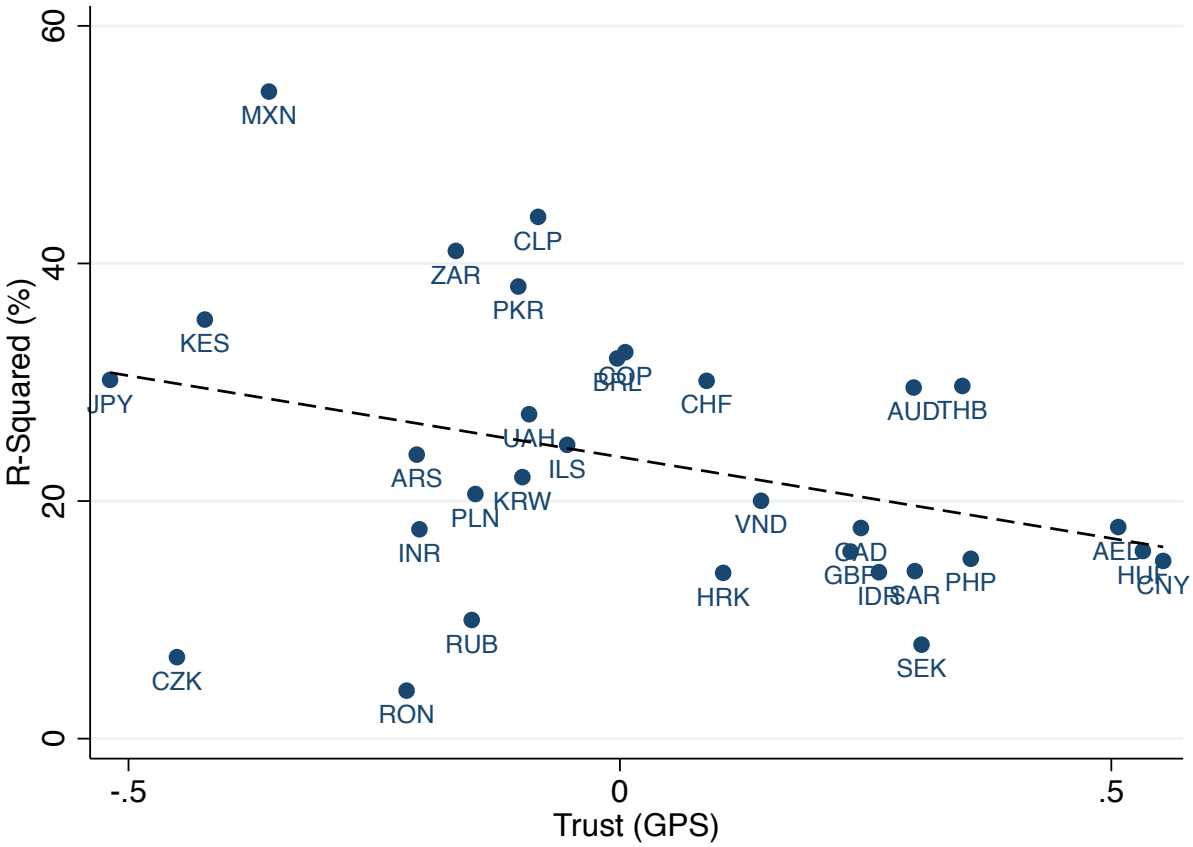
Figure A.13: Exchange Rate and Price Deviation




*Notes*: This figure plots coefficients $\beta_{c,t}$ in uni-variate regressions of price deviations on lead-lag exchange rate return.

$$Deviation_{c,t} = \beta_{c,t+i} Ret_{c,t+i}^{Currency} + \gamma_c + \epsilon_{c,t}$$

Figure A.14: In-sample R-squared and Trust

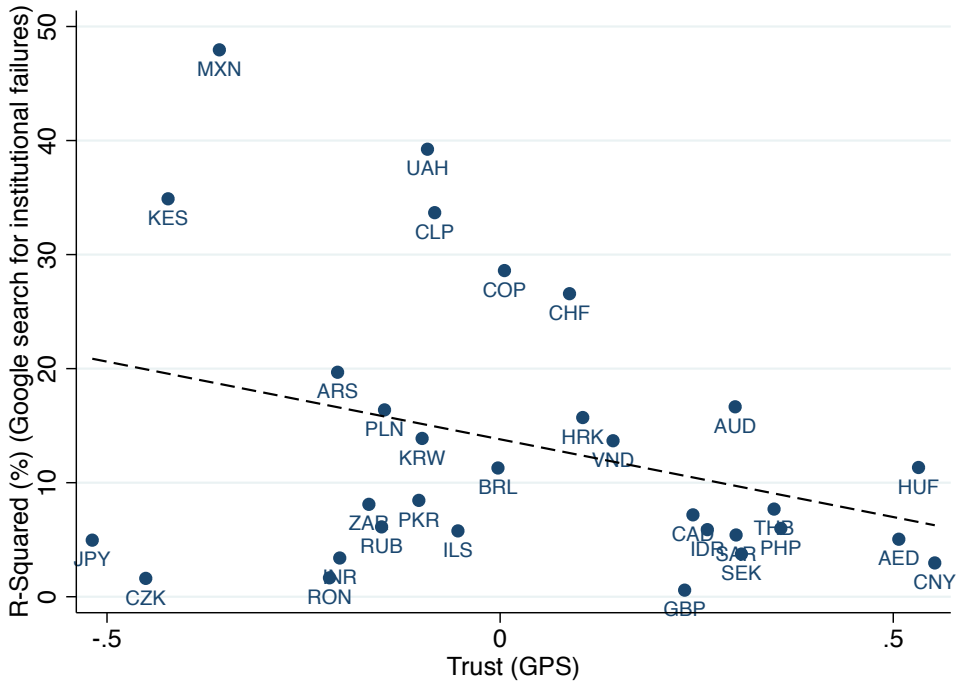



*Notes*: This figure plots the R-Squared obtained from the following regressions for each country against their trust levels.

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

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 A.15: In-sample R-squared and Trust (Google Search for Institutional Failures)

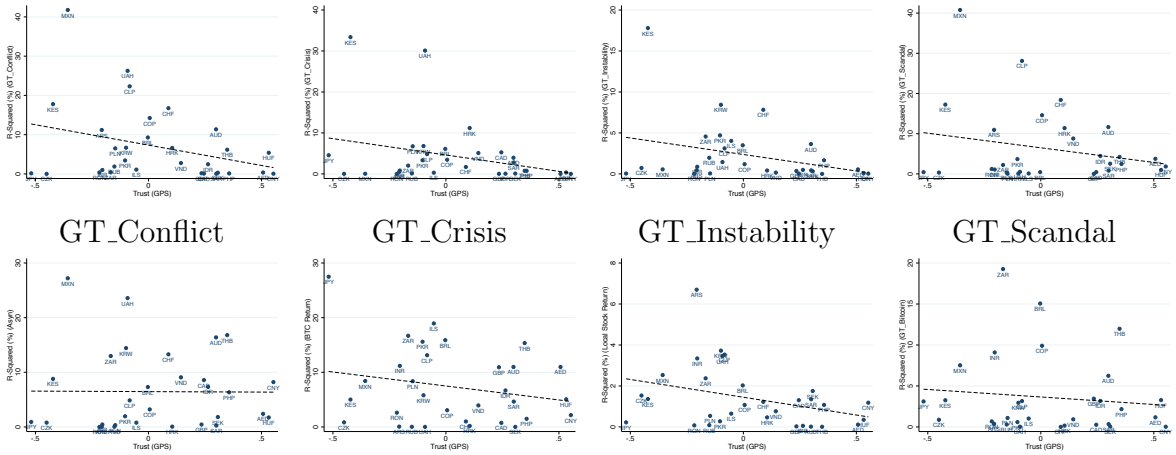



*Notes*: This figure plots the R-Squared obtained from the following regressions for each country against their trust levels.

$$\widehat{Deviation_t} = \alpha + \sum_{i=1}^{4} \beta X_{i,t} + \epsilon_t$$

where $X_{i,t}$ $(i = 1, 2, 3, 4)$ are the Google searches of keywords "Conflict," "Crisis," "Instability," and "Scandal" only.

Figure A.16: Uni-variate in-sample R-squared and Trust




GT_Conflict | GT_Crisis | GT_Instability | GT_Scandal

Asyn. | $Ret_{USD}^{BTC}$ | $Ret_{USD}^{Stock}$ | GT_Bitcoin

*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 A.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 A.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 A.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 C for the full list.

Table A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.15: Correlation between Crypto Returns and Stock Returns

| | Dependent Variable: $Ret^{Crypto}_{t-9\rightarrow t-1}$ | | | |
|---|---|---|---|---|
| | Weekly | | Monthly | |
| | BTC | ETH | BTC | ETH |
| | (1) | (2) | (3) | (4) |
| $Ret^{Stock}_{c,t-9\rightarrow t-1}$ | 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Ret^{Crypto}_{t-9\rightarrow t-1} = \beta Ret^{Stock}_{c,t-9\rightarrow t-1} + \epsilon_{c,t}$$

Table A.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 A.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%) |
| $Deviation_{c,t}$ | $3.06\times10^{-8}$ | 0.00427 | -0.00447 | -0.0296 | $5.77\times10^{-6}$ |
| | (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 A.18: In-sample R-Squared Analysis (Individual factor)

| | Dependent Variable: $\widehat{Deviation}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | All Countries | High-trust | Medium-trust | 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 A.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.

# B For Online Publication: Theory Appendix

## B.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 Proof of Proposition 2: Global and Local Risky Weights

We extend the framework into the multiple risky assets:

$$\max_{\pi_t} \pi_t'(\boldsymbol{r}_{t+1} - rf_{t+1})\boldsymbol{\iota} + \frac{1}{2}\pi_t'\boldsymbol{\sigma}_t^2 - \frac{1}{2}\pi_t'\boldsymbol{\Sigma}\pi_t + \frac{1}{2}(1-\gamma)\pi_t'\boldsymbol{\Sigma}\pi_t + \pi_t'\boldsymbol{p}\bar{\boldsymbol{b}} + \frac{1}{2}(1-\gamma)\pi_t'\boldsymbol{\sigma}_b^2\boldsymbol{p}\pi_t]$$

$\pi_t$ 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, $\iota$ 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 $\tilde{\mu_G} = \mu_G + \frac{1}{2}\sigma_G^2 - rf_L$, $\tilde{\mu_L} = \mu_L - rf_L + p\bar{b} + \frac{1}{2}(\sigma_L^2 + p\sigma_b^2)$

# C 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 billion investment. Vietnam happens to be building its 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 living, privatisation and inequality prevalent in the country | 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 | 2018.5 | | | N/A |

# D 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. |

# E For Online Publication: Blockchain, Cryptocurrency Storage, and Trading

## E.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.[57] 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.

## E.2 Options for Crypto-storage

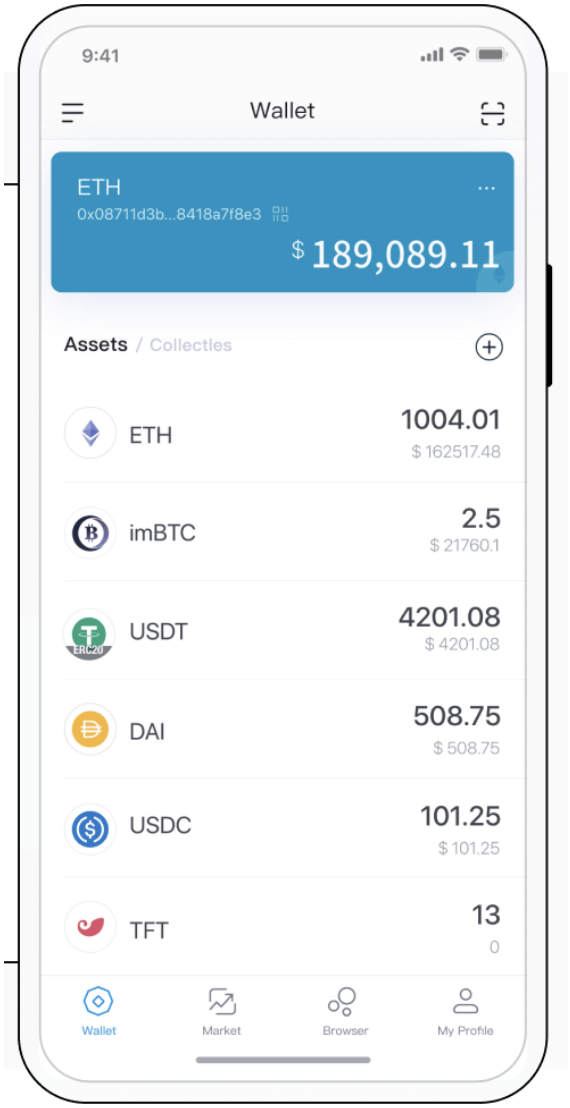
There are multiple ways to store private keys. Nowadays, the most common way to store cryptocurrencies is through cryptocurrency wallets. A cryptocurrency wallet can be a device, a physical machine, a software program, or a third-party service that stores private and public keys. Generally, all wallets belong to two types: centralized wallets and decentralized wallets. Centralized wallets, often

[57] Different PoS-based protocol may have different specific rules of consensus, but they all depend on the coins held on stake.

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 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 E.1 and E.2 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 E.1: Centralized Wallet

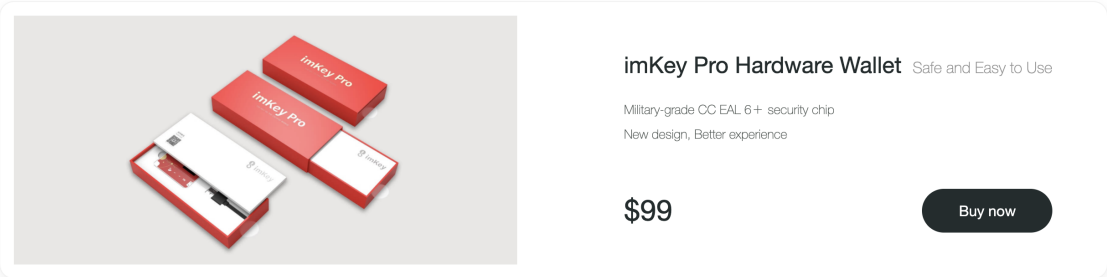



*Notes*: This figure shows an example of online "hot" cryptocurrency wallet.

## E.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

Figure E.2: Decentralized Wallet




*Notes*: This figure shows ImKey Pro, an example of offline "cold" cryptocurrency wallet.

this context, decentralization refers to no ownership delegation to the third party for trading. Currently, mainstream cryptocurrency exchanges are mostly centralized exchanges.[58] These exchanges 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.[59]

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 E.3 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.[60] Decentralized exchanges are slower than centralized exchanges but effectively eliminate the intermediation

[58] Large centralized exchanges include Coinbase, Binance, Huobi, Bitfinex, Kraken, etc.

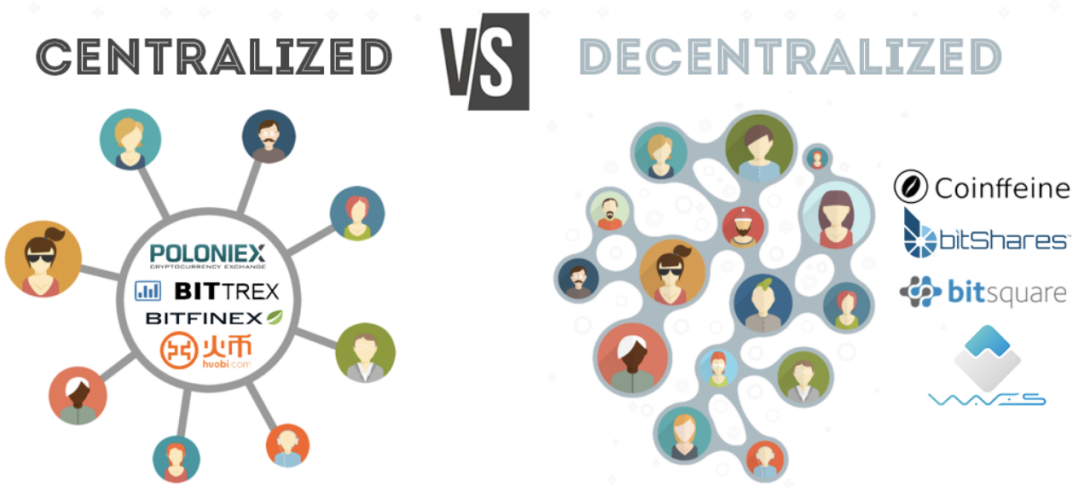
[59] For example, Coinbase, one of the largest cryptocurrency exchanges, and another 5 exchanges are under US regulations, and 26 cryptocurrency exchanges have got licensed in Japan by 2020.

[60] Pioneers of decentralized exchanges include Binance DEX, Newdex, WhaleEx, IDEX, DDEX, etc. Figure E.4 and E.5 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.

risk.

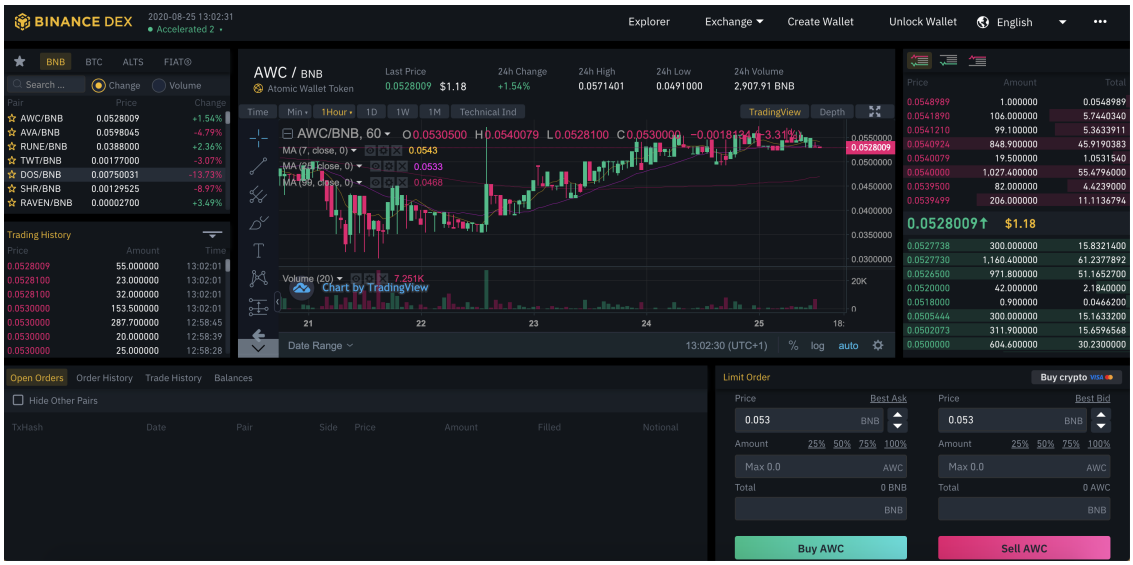
The last option is the OTC platform. OTC platforms differ from the centralized exchanges because the trade happens directly between two parties; they also differ from decentralized exchanges as they typically do not use blockchain technologies. Buyers and sellers can find advertisements that quote price 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 E.6 show the webpage of Localbitcoins.) post advertisements with much smaller cryptocurrency quantities in different countries.

Figure E.3: Centralized v.s. Decentralized



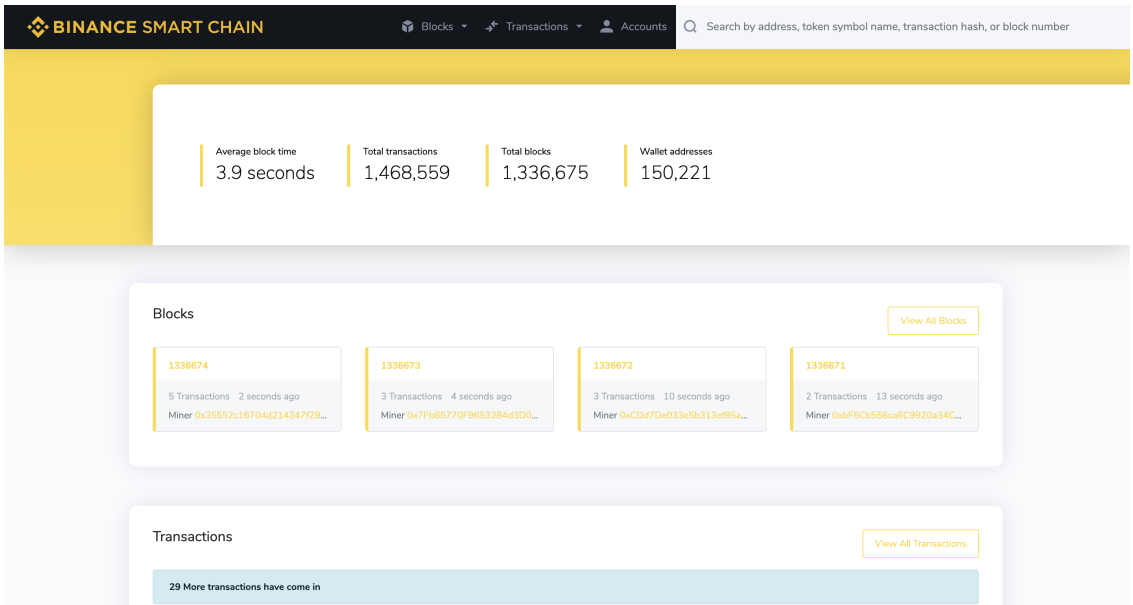

*Notes*: This figure shows differences between centralized and decentralized exchanges.

Figure E.4: Binance DEX



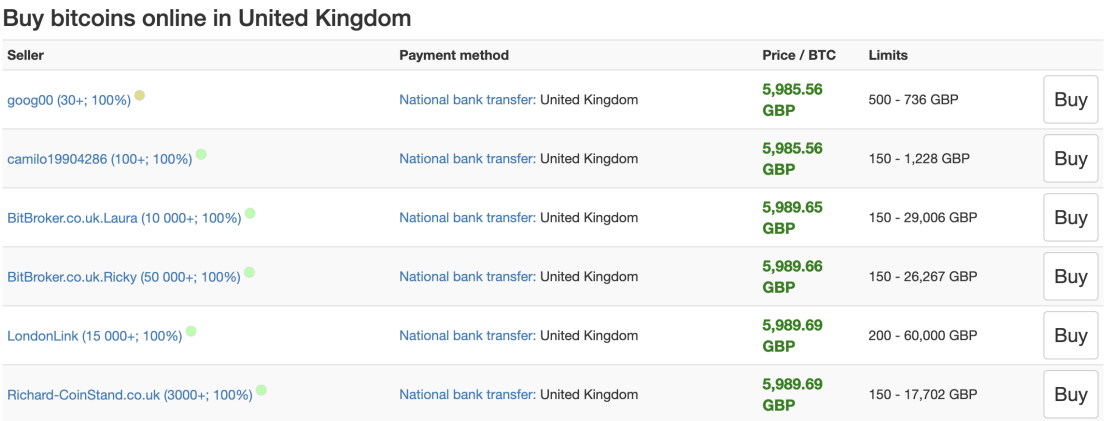

*Notes*: This figure shows the interface of Binance DEX.

Figure E.5: Binance Smart Chain




*Notes*: This figure shows the interface of Binance Chain's block explorer.

Figure E.6: 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.