Distrust and Cryptocurrency Price Deviations*

Bo Tang† Yang You‡ Yulin Zhong§

April 25, 2024

Abstract

Cryptocurrency prices differ across countries, and these price deviations fluctuate widely. Our paper provides evidence that distrust toward domestic authorities can explain the dynamics of local cryptocurrency prices relative to the U.S. dollar price. The price deviation rises after an outbreak of a financial crisis, political scandal, or socioeconomic event that undermines confidence in the domestic government or economy. With panel regressions, we show that Bitcoin price deviations increase by 1.8% when the institutional failure index rises by one standard deviation. These price responses are much stronger in countries with lower trust levels and during periods with tighter capital controls.

JEL-Classification: G12, G15, M14.

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

*We wish to thank Agostino Capponi, Andrea Carnelli, Jon Danielsson, 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, Gloria Yu, Kathy Yuan, Jinyuan Zhang and the seminar participants at the Chinese University of Hong Kong, Harvard University, London School of Economics, Pantheon, Peking University, and the University of Hong Kong, International Conference on Smart Finance (ICSF 2022) for their helpful comments and suggestions. First Draft: December 10, 2020.

†Luohan Academy of Alibaba Group; tangbo@alibaba-inc.com.

‡The University of Hong Kong, Faculty of Business and Economics; yangyou@hku.edu.

§The University of Hong Kong, Faculty of Business and Economics; zhongyul@connect.hku.hk.

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

The prominent economist Friedrich Hayek advocated the denationalization of money, arguing that governments "have instantly and everywhere abused their trust to defraud the people" (Hayek (1978)). Cryptocurrency supporters frequently refer to Hayek's view and argue that distrust in centralized authorities is the primary justification for Bitcoin and other decentralized tokens. Is there any empirical evidence that supports or runs contrary to this view?

In this paper, we focus on explaining the changes in local cryptocurrency price deviations—that is, the ratio of the cryptocurrency price in a local currency, converted into dollars at the real-time exchange rate, to the average worldwide dollar price.[1] Makarov and Schoar (2020) document the frequent occurrence of price deviations in many countries and highlight that the capital controls make prices differ across countries. Our paper further argues that distrust towards the government drives local cryptocurrency price deviations using a data set of Bitcoin and Ethereum trading from 31 countries.

We propose a simple conceptual framework to relate cryptocurrency price deviations with distrust. In the framework, we decompose distrust into two components: one dimension is the time-invariant probability of being confiscated by the government, proxied by the

[1] The fundamental premise is that cryptocurrency trading has frictions from 2015 to 2020 in many countries. Arbitragers cannot immediately equalize prices on exchanges in all countries. In Appendices C and D, we discuss the limits of arbitrage in cryptocurrency trading, various costs of cross-country arbitrage, and other legal risks of trading crypto in different countries.

survey-based trust measures; the other dimension is the time-varying perceived loss from government confiscation, proxied by the news about corruption or government scandals in the empirical analysis. Bitcoin serves as an alternative investment to the domestic risky asset. The domestic asset is subject to local government confiscation, while Bitcoin is not exposed to threats from the local government. The bad news about the government drives investors to shift their position from local assets to cryptocurrencies, and the incremental demand pushes up the Bitcoin price in the local market with limits of cross-country arbitrage. Our model further predicts that the crypto price deviation responses would be stronger in low-trust countries, as investors in the nation are more worried about political power abuse by the local authorities.

First, we test whether cryptocurrency price deviations are higher after events deteriorate the local government's credibility. To obtain the event list, we start with the Google Trends index of the keywords "conflict," "crisis," "instability," and "scandal" in these 31 countries, and manually look up actual events around all search peaks for these four keywords. Our event list excludes the socioeconomic events in the European Union and the United States because we calculate the price deviations based on cryptocurrency prices quoted in the US dollar and euro as the base currencies.[2] Out of 122 search spikes, 95 can be associated with events reported in news outlets, and 78 events are directly related to domestic politics and governments. Appendix B presents a detailed description of each event and whether this event induces distrust towards the local authority.

Our analysis starts with three major economic crises using Wikipedia's economic crisis list [3]: Brazil's economic slowdown[4], the Chinese stock market crash in 2015, and the severe devaluation of the Argentine peso in 2018. The 2018 Turkish currency crisis is excluded, as our cryptocurrency price data does not cover the Turkish Lira. In Argentina, the Bitcoin price premium rose to above 20% after capital controls were tightened in September 2019 in response to the peso's depreciation. In China, the Bitcoin price deviations rose over 2% in the

[2]Moreover, countries in the European Union share the same currency. It is hard to determine event in which country is strong enough to move the Euro cryptocurrency price.

[3]source: https://en.wikipedia.org/wiki/List_of_economic_crises

[4]The Bitcoin prices in Brazil were high during the crisis episode. However, we cannot identify events that induce distrust toward the government. Thus, we cannot obtain a difference-in-difference estimate for this economic crisis.

eight weeks after the largest single-day loss on August 24, 2015, and the subsequent Chinese government actions to penalize foreign capital and ban short-selling. In general, domestic cryptocurrency price deviation increases when there is a local economic crisis outbreak, particularly after the government imposes more limitations on capital flow in and out of the country.

Then, we analyze 39 political events that can possibly increase the domestic government's distrust level: 14 corruption scandals involving top politicians, 9 outbreaks of political protest, and 16 other forms of social unrest. The local Bitcoin price deviation was 199.86 bps (*s.e.*=56.45 bps) higher, and the Ethereum price deviation was 177.57 bps (*s.e.*=50.96 bps) higher on average in the eight weeks after the event was known to the public. Domestic cryptocurrency investors increased demand and temporarily drove up prices when they decided that local political authorities had lost credibility.[5] Some search peaks unrelated to trust in government, for example, food shortages, drought, and energy crises. 17 other search peaks were irrelevant events, such as the scandals of pop stars in the country. These events do not systematically weaken the government's credibility, and we see little impact on cryptocurrency price deviations.

To complement event studies, we estimate the price responses to the probability of institutional failure events using the entire panel data. We construct the institutional failure probability index (IFP henceforth) as the principal component of "conflict," "crisis," "instability," and "scandal" in Google Trends. Notably, our estimation with the panel data is a lower bound for the true impact as some events are not associated with the domestic authority. One core finding is that the deterioration of institutional quality drives local Bitcoin prices up: a one-standard-deviation increase in IFP corresponds to a 1.79% (*s.e.*=0.68%) higher Bitcoin prices and 1.21% (*s.e.*=0.43%) higher Ethereum price. The same effect also holds for all four keywords: a one-standard-deviation increase in searchers for "conflict" corresponds to a 1.49% (*s.e.*=0.65%) increase in the Bitcoin price deviation; similarly, increases of 0.67% (*s.e.*=0.32%) are seen for "crisis," 1.25% (*s.e.*=0.60%) for "instability," and 0.87%(*s.e.*=0.40%) for "scandal." In parallel, we find that trading volume modestly rises

[5] Carlson (2016) provides narrative evidence-based interviews that cryptocurrency does play a role in evading capital controls. The popularity of cryptocurrency is mainly attributable to high historical inflation, corruption, and other factors that disappoint domestic fiat currency users.

concurrently. Also, the search volume of keywords "Bitcoin" and "Ethereum" on Google increases during institutional failure events. These empirical findings suggest that higher local price deviations are likely driven by an increased domestic interest in buying cryptocurrencies. This is consistent with the economic mechanism highlighted in our model — the higher price deviations are driven by unusually high demand in the local crypto market.

Lastly, we show that the price deviation response to the IFP depends on the country's trust level in the country. Our baseline trust measure comes from the Global Preference Survey (GPS), which asks respondents whether they assume other people have good intentions.[6] We cross-validate our trust measure with the World Value Survey and find that it strongly correlates with higher trust in local institutions (civil service, government, banks, etc.) and lower perceived corruption in governments and civil services. The price deviation response is mainly concentrated in low-trust countries and diminishes or even disappears in high-trust countries: a one-standard-deviation increase in IFP corresponds to a 3.05% ($s.e.$=1.61%) higher Bitcoin price and a 1.97% ($s.e.$=0.74%) higher Ethereum price in 11 low-trust countries, but only a 0.31% ($s.e.$=0.36%) higher Bitcoin price and a 0.04% ($s.e.$=0.36%) higher Ethereum price in the high-trust countries. Similarly, IFP has much stronger explanatory power for the time-varying cryptocurrency price deviations in the low-trust countries, particularly Argentina (R-squared=23.8%) and Mexico (R-squared=20.1%), and the explanatory power is almost zero in high-trust countries. One concern is that trust might be correlated with other economic factors. To address this concern, we further horse-race trust with GDP, financial credit, the rule of law, government effectiveness, and control of corruption, and we show that trust is the most powerful indicator for explaining the heterogeneous response to IFP.

Our empirical results suggest that distrust-induced cryptocurrency demand is behind the larger price deviations over worldwide dollar prices. We further rule out several possible alternative mechanisms. First, simultaneous and future fiat currency depreciations are unlikely to explain IFP-induced local cryptocurrency price increases. In the panel data, the local currency's exchange rate (and its changes) cannot explain the cryptocurrency price deviation responses to the IFP. In addition, the price premium also cannot forecast further

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

currency returns. Second, the drying up of liquidity is not the reason for the widened price deviations. We find that trading volume modestly increases after outbreaks of political scandal and when the IFP is elevated. The rises in local cryptocurrency prices are more likely driven by stronger domestic demand rather than a reduced cryptocurrency supply. Lastly, we show that our results remain unchanged when controlling for the openness of capital accounts, and the price responses are more prominent when the government tightens the capital controls. This is consistent with the view that investors demand cryptocurrencies as a financial instrument to avoid the domestic government's control.

Our paper is closely related to three strands of the literature. First, we contribute literature on Bitcoin price deviations and the limits of arbitrage in cryptocurrency trading.[7] Makarov and Schoar (2020) pioneering paper is the first to systematically study price differences across currencies. Krückeberg and Scholz (2020) also identified the pattern of price deviation in the Bitcoin market. Several papers investigate why price deviations exist and persist. Goswami and Saha (2022) contends that Purchasing Power Parity holds for cryptocurrency. Choi et al. (2022) argues that capital controls and Bitcoin micro-structure jointly explain the Bitcoin price premium in Korea, and Eom (2021) propose that the elevated trading volume and price volatility can explain the Bitcoin price deviation in Korea. Hautsch et al. (2018) argue that blockchain settlement latency contributes to the limits to arbitrage. The remaining question is: what factor drives the price deviation changes over time, given the limits of arbitrage? Makarov and Schoar (2020) document widening deviations during a Bitcoin price rally. Yu and Zhang (2022) and Hu et al. (2021) show that Bitcoin price deviations increase with higher policy uncertainty. Nguyen et al. (2019) argue that the impact of monetary policy on prices varies across different countries. Borri and Shakhnov

[7]A vast body of literature studies the limits of arbitrage in 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 prices. Mitchell et al. (2002) and Lamont and Thaler (2003) provide evidence of the price differences in the stocks of a parent company and its subsidiaries. Reynolds et al. (2021) document significant deviations from triangular arbitrage parities in the newer markets for Bitcoin and Kristoufek and Bouri (2023) find that arbitrage opportunities arise when the network is congested and Bitcoin prices are volatile. Brauneis et al. (2018) and Shynkevich (2021) find that Bitcoin price varies in different exchanges, and Shu et al. (2023) proposes that investors from different bases react differently to market-related events, which create the price spreads between exchange platforms.

(2022) suggest that Bitcoin prices for more expensive pairs are riskier. Borri and Shakhnov (2023) argue that the variability of the cryptocurrency discounts is larger in countries with tighter capital controls. [8] Our paper highlights that price deviations are higher in events and episodes when local authorities' actions damage their credibility.

Our research is also related to studies on 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. (2022), and Caporale and Kang (2020)). Recent work argues that trust plays a critical role in financial intermediaries; 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.

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. The recent literature has discussed potential applications of blockchain to de-nationalized currency issuance (Harvey (2016), Budish (2018), Biais et al. (2019), Ferreira et al. (2022), Cong and He (2019), Cong et al. (2021), Abadi and Brunnermeier (2018), Easley et al. (2019), Sockin and Xiong (2023), Catalini and Gans (2020)), the role of cryptocurrency in the monetary system (Yermack (2015), Schilling and Uhlig (2019), Danielsson (2019)), and other forms of private money(You and Rogoff (2022)).[9] Our findings show that distrust of the domestic government feeds the demand for de-nationalized money.

Our paper is organized as follows. Section 2 describes cryptocurrency's data sources and price deviations. Section 3 presents a theoretical framework of crypto price deviations and distrust. Section 4 presents a series of event studies of major economic disasters, financial crises, and political scandals from 2015 to 2020 and quantifies their price impacts. Section 5 presents panel regressions of cryptocurrency price deviation on a time-varying institutional failure index constructed from Google Trends and explores heterogeneous responses regarding

[8] Williams et al. (2022) find that The strength of the BTC/CNY relationship is strongly and directly related to Chinese capital outflows, while there is no similar relationship with the Euro. Huang et al. (2022) contends that the deviation between actual and implied rates affects actual and BTC-implied rates.

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

cross-country trust levels. Section 6 rules out alternative explanations, as our findings are not driven by local fiat currency depreciation, liquidity, or changes in capital controls. Section 7 concludes the paper.

2 Data Description and Price Deviations

2.1 Cryptocurrency Price Deviations

We obtain volume-weighted Bitcoin and Ethereum daily prices quoted in different fiat currencies from the *CryptoCompare.com* API service.[10] Most crypto exchanges are not regulated and do not provide reliable historical price data.[11] Cryptocompare, a third-party real-time data aggregator, put together reliable price and volume data for different trading crypto-fiat sources for cross-country study. We use the daily exchange rate from Bloomberg to compute the local cryptocurrency prices converted into U.S. dollars and currency returns. We use the FX rate at the end of the previous trading date as the FX rate for weekends and holidays.

The Bitcoin prices quoted in different fiat currencies, converted into dollars with prevailing exchange rates, vary from country to country. On January 5, 2020, the Bitcoin price was 8,024.58 USD. However, Bitcoin traded at 11,101.39 SD equivalent (578,501.76 pesos) in Argentina, meaning that Argentine investors were willing to pay a 38% premium on that date. We define the price deviation as the price markup relative to the Bitcoin dollar price:

$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}} \times 10000$$

$Prc_{c,t}$ is the price in the local currency of country c, and $Exchange_{c-USD,t}$ is the exchange rate from Bloomberg.[12] In the robustness check, we construct the price deviations from the

[10] *CryptoCompare.com* computes the cryptocurrency prices by aggregating crypto-fiat currency trading pairs from different exchanges by the trading volume. See *https://min-api.cryptocompare.com/* for the API service we use.

[11] For example, Cong et al. (2023) document that unregulated exchanges use wash trading to increase their trading volume.

[12] 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.

cryptocurrency prices quoted in euro rather than dollar prices. We obtain five years (January 2015 - January 2020) of cryptocurrency closing prices (ETH prices are only available since August 2015) and trading volumes from CryptoCompare.[13] In this research, we first calculate the daily price deviation and then calculate the weekly average price deviation data to smooth the change in cryptocurrency prices. $Deviation_{c,t}$ has the unit of basis point and should always equal 10,000 if the law of one price holds perfectly in all countries.

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. The price difference was only 2.16% in the United Kingdom simultaneously. Argentine Bitcoin prices are also much higher and more volatile than the U.K. Bitcoin prices over time. Table A.1 Panel A presents the summary statistics of price deviations across 31 countries in our sample. The average price deviation across all countries is 3.12%, and the standard deviation is 13.25%. Argentina has the most expensive Bitcoins: it is 12.07% more expensive on average to buy Bitcoins there than in the United States. Colombia has the cheapest Bitcoins: they are 3.51% cheaper than U.S. Bitcoins on average. Moreover, BTC and ETH price deviations are 90.98% correlated, and such a high correlation implies that a country-specific component drives the time-varying price deviations, consistent with Makarov and Schoar (2020).[14]

2.2 Institutional Failures

We use weekly Google Trends indices of the keywords "conflict," "crisis," "scandal," and "instability" to capture the probability that institutional failure events happen.[15] The maximum of an index scales to 100 given the sample period from January 2015 to January 2020. We run two sets of analyses with these four Google Trends indices. First, we manually look

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

[14]We present the trend of the median number of price deviation of BTC and ETH in Figure A.2. The trend for BTC's median number of price deviations is also highly correlated.

[15]When the domestic probability that institutional failure events happen is high, the English media will report the event and trigger the increase of the Google Trends index. Therefore, we can exclude the events that do not undermine trust in government. Additionally, we can only manually identify the news in English rather than in the local language related to the events.

up all search peaks for our four keywords and construct a database for the event studies, as presented in Section 4. Some events will hurt domestic institutional quality, such as financial crises, corruption scandals, and some political events, while other events are irrelevant to local institutions, such as drought, pollution, or pop star sex scandals. Second, we use the principal component analysis (PCA) to extract a time-varying composite index to capture the probability of institutional failures and analyze its relationship with price deviations in the panel data in Section 5.

2.3 Trust and Other Country Characteristics

To explore cross-country heterogeneity, we obtain a set of country characteristics. Trust data are taken from the Global Preference Survey (GPS).[16] This survey asked respondents whether they assume that other people only have the best intentions, which captures the general distrust level. We obtain other more granular trust-related variables — confidence in various local institutions and perceived government corruption— from the World Value Survey (WVS) to validate our baseline trust measure. In the WVS, each respondent provides their confidence level in banks, companies, government, politics, and civil service. We assign a score 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." For each country, we use the average score from all of the respondents in the country to proxy for the confidence level. Similarly, for each question about perceived corruption in business, civil service, and local and state government, we assign a score of 2 to "None of them," 1 to "Few of them," -1 to "Most of them," -2 to "All of them," and 0 to "Don't know" or "No answer". Perceived corruption control is the average score of the respondents in each country.

The capital control measure is based on the Chinn-Ito index, which measures a country's degree of capital account openness. It is constructed from binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions. For each

[16] The Global Preferences Survey is a globally representative survey of 80,000 individuals on risk and time preferences, positive and negative reciprocity, altruism, and trust in 76 countries worldwide. See Falk et al. (2018). The trust level ranges from -1 to 1.

country in our sample, we obtain its yearly data on capital openness so that the capital control measure is in the panel data format. We also obtain cross-sectional country features. Data on GDP per capita, and credit by the financial sector are from the World Development Index. The rule of law, government effectiveness, and corruption control scores are from Worldwide Governance Indicators.

We match price deviations by currency with Google Trends indices, trust data, exchange rate, trading volume, cryptocurrency returns, capital control, and country features. There are 31 countries (excluding the U.S. and countries in Eurozone) left in our sample: Argentina, Australia, Brazil, Canada, Chile, China, Colombia, Croatia, the Czech Republic, Hungary, India, Indonesia, Israel, Japan, Kenya, Mexico, Pakistan, the Philippines, Poland, Romania, Russia, Saudi Arabia, South Korea, Sweden, Switzerland, Thailand, Ukraine, the United Kingdom, the United Arab Emirates, Vietnam, and South Africa.

3 Conceptual Framework

We build a stylized model of cryptocurrency investment to relate cryptocurrency price deviations with local *time-varying* institutional failure and *time-invariant* country-level distrust. We consider a portfolio choice model with two risky assets: one is the domestic risky asset subject to local government extortion, and another risky asset is a cryptocurrency, immune from local government disruption but facing arbitrage frictions across countries. Distrust is the perceived probability of the government exploiting their investment in risky assets (e.g., local public firms). We assume that distrust is time-invariant over time in a given country. The institutional failure news affects people's belief about how much they will lose if they are exploited; for example, a corruption scandal outbreak leads investors to believe they will lose more wealth if the corrupt politicians seek rent from their investments.

3.1 Model Setup

3.1.1 Assets

Three assets are available for investors. A risk-free asset offers a return R_f ($r_f = log(R_f)$) and is immune from local government confiscation, e.g., U.S. Treasury bill. There are two types of risky assets in the economy. One is the local risky asset return R_L follows a log-normal distribution: $log(R_L) \sim N(\mu_L, \sigma_L^2)$. The local risk is exposed to the government's rent-seeking: Investors perceive an exploitation probability of p and can only recover e^κ ($\kappa < 0$) percentage of investment return if being exploited by the government. The other risky asset is Bitcoin, and its return R_B follows a log-normal distribution $log(R_B) \sim N(\mu_B, \sigma_B^2)$. Bitcoin is not exposed to exploitation by the government, and μ_B and σ_B are exogenous parameters as they are determined by traders worldwide in the long run.

We make an important assumption here: Bitcoin functions as a substitute for the local risky asset; that is, cryptocurrency returns are positively correlated with the local stock returns: $Corr(R_B, R_L) = \rho > 0$.[17] Under this assumption, investors would substitute local investments with cryptocurrencies when they perceive higher losses from exploitation in their home countries.

3.1.2 Investors

We consider a representative cryptocurrency investor who is myopic with constant relative risk aversion (CRRA) γ. The investor optimizes the portfolio choice from all three assets by maximizing the expected utility: π_B of wealth invested in cryptocurrency, π_L of wealth in local risky investments, and the rest allocated in the risk-free asset. For simplicity, we assume that the investor does not consider transitory price deviations for portfolio construction; that is, Bitcoin demand π_B is inelastic to the price deviation.[18]

[17] The ρ is positive in the data. We compute the monthly return between Bitcoin and stock return indices in 24 countries. We find ρ is positive for 23 countries among them. The average correlation is 18.31% (s.e.=2.24%)

[18] 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.

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

3.1.3 Supply Curve

Then, we assume arbitragers face a linear supply curve of cryptocurrency in the domestic market:

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

where $\frac{P_L}{P_{USD}}$ is the transitory price deviation and $S - \bar{S}$ captures the excess Bitcoin supply provided by arbitragers. $\bar{S}$ is the Bitcoin supply in the steady state, and arbitragers react to the price deviations and supply additional Bitcoins to clear the local market so that $S = \pi_B$. When the local demand surges, arbitragers must provide more Bitcoin in the local count, and a larger price difference is required for arbitragers to bring more Bitcoin.[19] K is a parameter that reflects the limits of arbitrage discussed in Appendix C — when market friction increases, a higher K indicates a larger price change given the same demand shock.

3.2 Asset Allocation and Distrust

Then, we are ready to investigate how distrust in the local government affects Bitcoin demand. Proposition 1 solves the portfolio weight of Bitcoin as follows:[20]

$$\pi_B = \underbrace{\frac{1}{\gamma\sigma_B^2}\frac{\sigma_L^2(\mu_B + \frac{1}{2}\sigma_B^2 - rf_L) - \rho\sigma_L\sigma_B(\mu_L + \frac{1}{2}\sigma_L^2 - rf_L)}{(1-\rho^2)\sigma_L^2}}_{\Pi_G^B\text{:Bitcoin Demand without Distrust}} \quad - \underbrace{\frac{1}{\gamma\sigma_B^2}\frac{\rho\sigma_B\sigma_L}{(1-\rho^2)\sigma_L^2}}_{\chi\text{:Lower Return Induced by Distrust}} \quad p\kappa$$

Comments: The first term Π_G^B is the demand under a perfect trust ($p = 0$) in the local authority. The second term χ is the demand induced by the government confiscation to the average loss from exploitation $p\kappa$. χ is also positively correlated with ρ[21] which captures the

[19] Without losing generality, our model assumes only arbitragers respond to price deviations while investors' demand does not change according to transitory price deviations.

[20] See Appendix E for math derivation.

[21] The positive correlation is evident by rewriting the formula as $\frac{1}{\gamma}\frac{\rho}{1-\rho^2}\frac{1}{\sigma_L\sigma_B}$. $\frac{\rho}{1-\rho^2}$ is an increasing function

substitution effect between Bitcoin and the local risky asset investment. When a political scandal occurs, an increase in κ makes investors more pessimistic about the local risky asset and purchase more Bitcoin as a substitute in their risky asset portfolio.

3.3 Empirical Predictions

We relate the Bitcoin price deviations to the distrust through the local Bitcoin supply curve.

$$\frac{P_L}{P_{USD}} - 1 = K(-\chi p \kappa + \Pi_G^B - \bar{S})$$

To relate with the empirical setting, κ captures the time-varying perceived exploitation loss: investors keep learning how large the rent-seeking exists in the economy. For example, a corruption scandal can inform investors about how much bribery corrupt politicians take from domestic firms. p is the time-invariant distrust of government, but it varies across countries. $\bar{S}$ is the time-invariant equilibrium Bitcoin supply in the country. We make the following two empirical predictions about price deviations related to time-varying news on government credibility κ and heterogeneous effects by distrust level p:

Prediction 1: Information on institutional failure news induces a higher price deviation:

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

Prediction 2: Price deviation response to institutional failure news would be stronger in economies with higher distrust:

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

Section 4 tests the first prediction with event study analysis of news related to institutional failures inducing a higher price premium in the local country. In Section 5.2, we construct panel data to show that price deviations increase when Google searches about institutional failures are higher. To test the second prediction, we introduce a survey-based

in ρ.

slow-moving trust variable in Section 5.3 and show that cryptocurrency price deviation responses are stronger in low-trust economies.

4 Event Studies

We manually look for the events around the Google search spikes of the keywords "conflict," "crisis," "instability," and "scandal" for all countries. In total, we find 122 Google search spikes. We successfully identify 95 events, while the other 27 peaks cannot be associated with any news, and we report the details of these events in Appendix B. Of these 95 events, 78 events out of 95 are directly related to local institutions or politics. Almost no domestic search spike is linked to international news or events in other countries. The other 17 events are irrelevant to the government; these include sexual scandals involving pop stars, corrupt sports teams, etc. We end with classifying all 122 spikes into four categories and study price deviation responses to (1) three major economic and financial crises, (2) political scandals, (3) other social-economic events, and (4) irrelevant and other unknown events .[22]

We exclude the events happened in the United States and Eurozone. For the United States, we need to have a benchmark Bitcoin price to use, and inevitably, we use the US dollar price as the international price. Thus, we are not able to study any US events. For the Eurozone, we only have data for the Bitcoin-Euro trading pair and we cannot aggregate the Google Trends and trust variable for the Eurozone. Therefore, we exclude the Eurozone events and use euro as an alternative benchmark Bitcoin price.

4.1 Major Economic and Financial Crises

We start with three economic and political crises using Wikipedia's economic crisis list[23] : Argentina's monetary crisis, the Chinese stock market crash, and Brazil's economic slowdown. Wikipedia also lists the Turkish currency and debt crisis in 2018; however, we do not have cryptocurrency prices quoted in Turkish lira.

[22]Appendix B also lists the Google Trend peaks that cannot be linked to any event with our best effort.
[23]https://en.wikipedia.org/wiki/List_of_economic_crises

4.1.1 Argentina's Monetary Crisis and Capital Control

In 2017, the annual inflation rate in Argentina reached 25%, and the currency depreciation triggered Argentina's peso crisis. On September 1, 2019, Argentina's central bank announced new restrictions on foreign currency transactions. Mauricio Macri, the President of Argentina, required the companies to seek permission from the central bank to purchase foreign currency. The new regulation also limited individuals to purchasing a maximum of USD 10,000 per month. Argentina's Chinn-Ito capital account openness index dropped from 1.549 in 2018 to -0.726 in 2019.

Cryptocurrency provides an instrument for domestic peso holders who want to hold an asset not subject to peso depreciation or evading tightened capital controls. Thus, cryptocurrency became more desirable to domestic investors, particularly when Argentinians found all domestic investments denominated in peso devalued. Figure 1 shows that the BTC and ETH price deviations increased from 6% to 13% after tightening the capital control on September 1st, 2019.[24] We do not find any simultaneous price premium change in a placebo test with the median price deviation of all other countries.

One concern is that the official exchange rate of the Argentine peso is not the actual market exchange rate. To address this concern, we recalculate the premium of cryptocurrencies in Argentina using the black-market rate obtained from the Blue Dollar website.[25] Figure A.4 Panels A and B plot the recalculated BTC and ETH price deviations increased by 9% on average in the first six weeks of implementing stricter capital controls. The jump in price deviation is robust.

[24] We also examine Argentina's capital control policy over time and find that capital account liberalization started in 2015. Back in 2011, the government, led by Cristina Fernández de Kirchner, restricted the purchase of U.S. dollars by forbidding the practice except in a limited number of cases. From 2012 to 2015, the Chinn-Ito index held steadily at -1.93. On December 17, 2015, the government, led by Mauricio Macri, lifted the currency controls and allowed the peso to float when markets opened to increase exports and spur economic growth. The Chinn-Ito index also indicates that capital control persistently eased until the currency crisis in 2019, as the index values were -1.234 in 2016, 1.295 in 2017, and 1.549 in 2018. Figure A.3 plots the premium in the 16-week time window around December 13, 2015. The BTC and ETH price deviations steadily dropped from about a 53% premium in October 2015 to 3% in February 2016 in response to loosening capital controls.

[25] https://bluedollar.net provides the best price one can get if one wants to buy or sell Argentine pesos, and the transaction is done with no involvement of any government-sanctioned or licensed entity.

4.1.2 The 2015 Chinese Stock Market Crash

The Google Trends "crisis" peaked in China in August 2015, and the timing corresponds to the Chinese stock market bubble crash. The SSE composite index fell by 8.48% on August 24, 2015, after the Chinese government took many actions to stabilize the capital market but failed to stop the stock prices from freefalling. August 24 marked the largest single-day drop since the 2008 Global Financial Crisis.

The Chinese government took several legal actions against practitioners and corrupt government officials accountable for the market collapse.[26] To limit the market meltdown, the government unexpectedly limited the freedom to sell Chinese stocks, making shorting-selling more costly or even impossible in the derivative market.[27] The price drop and unpredictable changes in trading restrictions frustrated investors and added more pessimism to the domestic capital market.

Figure 2 plots the price deviations around August 24, and we find that Bitcoin and Ethereum traded relatively more expensively than international prices after the stock market crash by roughly 2%. The price increase cannot be explained by investor sentiment or speculation, as Chinese stocks were dramatically devalued. Also, there is no sign of changes in capital control in response to the stock market crash.[28] Our evidence suggests that pessimism about capital market governance increased cryptocurrency demand in China.

[26]On July 3, 2015, the state-owned Chinese media outlet*Financial News* posted an article, "No time to lose in the fight against malicious short-selling." Meanwhile, the China Financial Futures Exchange started to examine accounts that made short-selling bets. On the same date, Qingfeng Meng, Vice Minister of Public Security of the People's Republic of China, collaborated with the China Securities Regulatory Commission to investigate reports of malicious selling of stocks and stock indices. By August 30th, the Chinese regulators had arrested 197 people, including Xiaolu Wang, a journalist at Caijing Magazine (a leading independent financial media), and several government officials in China Securities Regulatory Commission (the Chinese stock market regulator), for spreading "rumors" about the stock market crash.

[27]On July 31, the Shanghai Stock Exchange and Shenzhen Stock Exchange announced trading restrictions on ten accounts identified with significant unusual trading behavior. On August 1, the China Securities Regulatory Commission announced that it had taken restrictive trading measures on 24 accounts that engaged in algorithm trading and blamed foreign capital for triggering the market crash. On the evening of August 2, Citadel confirmed that its account had been restricted from trading by the Shenzhen Stock Exchange.

[28]The Chinn-Ito index (*kaopen*) in China is a constant -1.234 from 2015 to 2020. Due to China's strict capital controls, we additionally utilize the offshore exchange rate of the Chinese Yuan to recalculate the premium of cryptocurrencies. Figure A.4 Panels C and D demonstrate that the recalculated BTC and ETH price deviations increased by 3%.

4.1.3 Brazil's Economic Recession

We pick up Brazil's economic recession with a Google search of "crisis" beginning in June 2014. The Brazilian GDP decreased from 2.46 trillion to 1.8 trillion Brazilian Real from 2014 to 2016. Meanwhile, the unemployment rate increased from 6.7% to 11.6%, and inflation rose from 6.3% to 8.7%, respectively. Figure 3 plots the trend of Bitcoin price deviations and relates them to the (normalized) exchange rate and Brazilian GDP from April 2015 to April 2017 in Brazil.[29] The cryptocurrency price deviations remained high from November 2015 to June 2016 after rapid currency depreciation and economic recession. We run the following time-series regression to examine the relationship between the price deviations and the Brazilian real exchange rates:

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

Table A.2 shows that the cryptocurrency deviations are negatively correlated with the normalized exchange rate of the Brazilian real. In Column (1), the naive time-series regression implies that 1% depreciation corresponds to a 10.80-bps ($s.e. = 4.27$) higher BTC premium and 11.07-bps ($s.e. = 5.14$) higher ETH premium. In Column (2), we add the simultaneous Brazilian currency return to the regression, and we find that the coefficients of the exchange rate index remain stable: 11.61 bps ($s.e. = 4.20$) for BTC and 12.84 bps ($s.e. = 5.12$) for ETH. Cryptocurrency prices in Brazil are very inefficient as the simultaneous currency return has a roughly 40% pass-through (39.64% for BTC and 42.75% for ETH) to the cryptocurrency price deviations. Thus, the fiat currency depreciation would mechanically drive the price deviations down instead of pushing them up; therefore, the currency depreciation itself cannot explain any of the increase in price deviations it generates. In Column (3), we add the quarterly GDP to the regressions and document that 1% depreciation corresponds to 11.72 bps ($s.e. = 4.37$) for BTC and 14.42 bps ($s.e. = 5.61$) for ETH conditional on the GDP level. A GDP decline also positively contributes to higher price deviations with limited statistical power. Our evidence suggests that a radical cur-

[29]The quarterly GDP started to stabilize and recover from 2017Q1 to 2019 Q4 by 4%. The Brazilian GDP and currency dropped quickly from April 2015 to February 2016.

rency depreciation could sufficiently boost an excessive cryptocurrency demand to offset its downward pressure on local Bitcoin and Ethereum prices.[30]

4.2 Political Scandals

In addition to the three crises studied above, we find 43 events related to politics and manually validate whether these political events are bad news that impairs government credibility. Among them, 14 events are corruption scandals, 9 are outbreaks of political protest, and 16 are other forms of social unrest.[31]

For each event, we track the changes in price deviation in an event window of 16 weeks. Figure 4 plots the average (equal-weighted) price deviation of all 43 political events. We find a consistent pattern in which BTC and ETH (solid lines) price deviations drift after the Google search spikes. As a placebo test, we plot the median price deviations of all countries (dashed lines) in the same time window of these political events. We find no significant rise or a much smaller increase in the all-country median price deviation. The local cryptocurrency prices started to rise before the event date as the largest search volume on Google is typically later than the onset of the political event. One example is the Marawi Conflict in the Philippines: the attention on Google reached the highest level six weeks after the war began. Figure A.6 shows that cryptocurrency price deviations rallied significantly after the war began but fluctuated after the Google search peak. These mis-specified event

[30] Our keyword search approach does not identify any specific event or policy changes in Brazil (the Chinn-Ito index has held at -1.234 since 2015). Yu and Zhang (2022) study three political crises in Brazil: Operation Car Wash, which resulted from a leak on March 17, 2014; the Brazil Labor Reform proposed on December 23, 2016; and the protests against reforms that erupted on March 15, 2017. We validate their results with our data. Figure A.5 plots the gap between the Bitcoin price deviation and global median deviation within the eight weeks following each event date. The gap between Brazil's Bitcoin price deviation and the market median became larger within two weeks after each event. The price deviation gap jumped from -2% to 3% in the week of March 17, 2014, and further to 10% in the next eight weeks for Operation Car Wash. Brazilian president Michel Temer proposed labor reform to combat unemployment and economic recession on December 23, 2016. In the week of the labor reform proposal submitted to the Chamber of Deputies, the gap jumped from 2% to 8%, but it quickly reverted to the pre-reform level in the next three weeks. The labor reform was controversial, as many critics argued that it violated the Brazilian constitution and international labor conventions. An outbreak of protests against labor reform occurred on March 15th, 2017. After the protests, the gap jumped from 1% to 7% and drifted to 15% after eight weeks.

[31] The remaining four events would not induce distrust: Thailand's crackdown on corruption in March 2017, the Qatar–Saudi Arabia diplomatic conflict (identified in the UAE in June 2017 and Saudi Arabia in August 2017 with Google Trends), the ceasefire deal between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC) in July 2016.

dates might explain the pre-trend and lead us to underestimate the price impacts of these political events, and our estimates provide a lower bound.[32]

Table 1 Column (1) estimates the average price deviation change of political events. Bitcoin price deviations are 199.86 bps ($s.e. = 56.45$) higher, and Ethereum price deviations are 177.57 bps ($s.e. = 50.96$) higher in the eight weeks after the event date. Cryptocurrency prices increased when domestic investors witnessed political scandals and had less confidence in their home country. We further run several robustness checks. First, we compute the adjusted price deviations as the raw price deviations minus the international median price deviation that week and replicate the same event studies. The BTC-adjusted deviations rose by 137.05 bps ($s.e. = 41.43$), and ETH-adjusted deviations rose by 101.35 bps ($s.e. = 33.03$). These coefficients are statistically significant with a slightly smaller magnitude. Then, we exclude the four events that do not induce distrust and report the results in Table A.3. Price deviations increased by 203.493 bps ($s.e. = 56.45$) for BTC and 174.81 bps ($s.e. = 54.72$) for ETH.[33] Last, we re-estimate the coefficients with deviations against euro crypto prices in Table A.4 and obtain similar results: 199.92 bps ($s.e = 55.78$) for BTC and 152.52 bps ($s.e = 48.60$) for ETH.

We also find that attention to Bitcoin increased after the outbreak of these political events, indicating more interest in cryptocurrency trading. Table A.5, Column (1) reports the event studies of the Google Trends indices of "Bitcoin" and "Ethereum." The index increases by 5.09 ($s.e.$=2.04) units for political events, corresponding to a 0.34 standard deviation more attention to Bitcoin on Google; similarly, the coefficient is 6.41 ($s.e.$=2.61), 0.37 standard deviations more attention to Ethereum. People also pay more attention to gold but with a much smaller magnitude: 1.19 ($s.e.$=0.68) units correspond to only a 0.08 standard deviation increase.

[32] In addition, some events might not be significant enough to change the price deviation in that country. One example is the Indian-Pakistan Conflict. Figure A.7 shows the trend of Bitcoin price deviation from January 25, 2015, to May 17, 2015, in India and Pakistan. Bitcoin became roughly 10% more expensive in Pakistan during the conflict, while the price deviations did not move much in India. Given that India is much larger than Pakistan, the same conflict may trigger more panic in Pakistan than in India.

[33] We plot the four political events that do not induce distrust in Figure A.8. The price deviations do not systematically increase after these four events.

4.3 Other Keyword Search Peaks

There are other search peaks corresponding to different events, and we further classify them into socioeconomic events, irrelevant events, and other unknown events. We find that only government-related socioeconomic disruptions induce a rise in the local crypto-prices, while other events do not trigger significant changes.

4.3.1 Other Socioeconomic Events

We identify 11 other socioeconomic events and classify them into two event groups depending on whether the event is related to the government. Five events are associated with the government: the UAE economy slowdown reported in December 2017, the Brazilian sovereign credit rating downgrade in December 2015, the Colombian peso depreciation in August 2015, the severe economic downturn in India in December 2019, and the Indian stock market crash in February 2016. Table 1 Columns (2) and (3) report the regression analyses of events related and unrelated to the government and not associated with the government on price deviations, respectively. For events related to the government, there is an average of 216.37 bps ($s.e. = 70.31$) higher Bitcoin price deviations and 236.39 bps ($s.e. = 85.51$) higher Ethereum price deviations in the eight weeks after the event date.

There are six events unrelated to the government: the illegal migrant crisis in Australia in June 2015, U.S. President Trump's steel tariffs on Brazil in December 2019, the British homelessness crisis in November 2017, the Indian milk crisis in June 2015, the drought in Kenya in June 2019, and the subsequent Kenya food crisis in December 2019. There are no significant increases in BTC and ETH prices in the eight weeks after these event dates.[34] Consistent with our findings for political events, we only find positive price impacts for events tied to domestic authorities.

[34] Figure A.9 plots the event studies of socioeconomic events related to government and those not related to government. We do not find local cryptocurrency price rises for government-unrelated events.

4.3.2 Irrelevant and Unknown Events

We also identify 17 events not related to economics and politics. These irrelevant events include five sex scandals, five company scandals, three environmental crises, two sports scandals, and two other unclassified events. Table 1 Column (4) shows almost no price impacts of these 17 events. We further break down our analysis by event type and study the impact of each kind in Figure A.10. The Bitcoin price deviations modestly increase but are not statistically significant for company scandals and environmental crises, and we find no changes after the sex and sports scandals. Figure A.11 plots the price dynamics of irrelevant events; similarly, we do not observe price deviation increases.

Still, 17 search peaks cannot be associated with any event after our best manual search on Google. No actual event may be associated with the index surge (pure noise in the data), or no news in English is available on Google. Table 1 Column (5) indicates that the cryptocurrency price deviations do not respond to these unknown Google Trends search peaks.[35] Overall, crypto prices do not rise if these search peaks do not match events related to distrust of local government.

5 Panel Regressions

This section extends our analysis to test both predictions with the full panel data. The panel data enables us to test whether Google searches of institutional failures have the statistical power to explain the cryptocurrency price deviations. Moreover, we can introduce country-level trust to the panel data and formally test the second prediction.

5.1 Institutional Failure Probability Index

We construct the institutional failure probability (IFP) index from the Google Trends indices for "conflict", "crisis," "instability," and "scandal" to capture the time-varying distrust

[35] Figure A.12 plots the average price dynamics of Bitcoin and Ethereum; no price deviation response is also observed.

κ.[36] To smooth out the Google Trends, we first compute the cumulative Google Trends index $GT_{c,t}$ as a discounted sum of Google search indices in the past eight weeks with a discount factor of 0.8.[37,38]

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

Then, we run a principal component analysis (PCA) on the cumulative Google Trends index of "conflict," "crisis," "instability," and "scandal," to obtain the first component as the institutional failure probability (IFP) index.[39] Lastly, to make the coefficients interpretable, we normalize IFP and all $GT_{c,t}$ by their means and standard deviations. Section 6.2 provides a further discussion on the validity of the IFP index.

5.2 Price Deviations and IFP Index

To test Prediction 1 in panel data, we regress cryptocurrency price deviations on IFP and cumulative Google search indices one by one. To set a high bar for statistical significance, we report two-way clustered standard errors at both currency and week levels and adjust for all regressions throughout the paper.

$$Deviation_{c,t} = \beta IFP_{c,t} + \gamma_c + \epsilon_{c,t} \tag{2}$$

Table 2 reports the results of our baseline regressions. In Panel A, a one-standard-deviation increase in IFP corresponds to a BTC price deviation increase of 179.00 bps($s.e.$=68.18). The BTC price deviation expands by 149.78 bps ($s.e.$=64.67), 67.09 bps ($s.e.$=32.26), 125.198 bps ($s.e.$=60.41), and 87.50 bps ($s.e.$=39.70) when the search indices of "conflict," "crisis," "instability," and "scandal" rise by one standard deviation, respectively. In Panel B, the

[36] Our event study analysis shows that these keywords successfully capture events associated with the government. However, Google Trends data also pick up some noise (e.g., sports and sexual scandals) that do not harm the credibility of the local government, which tends to bias our estimation toward zero. Thus, our panel data analysis tends to underestimate the true effect.

[37] Our results are not sensitive to the choice of the discount factor of 0.8. As Table A.6 shows, our baseline results hold for other deflators from 0.2 to 1.

[38] $Google_{c,t}$ denotes the raw Google Trend index for country c and week t.

[39] Table A.7 reports the correlation of the IFP and cumulative Google Trends index for the four keywords.

ETH price deviations yield similar responses: a one-standard-deviation increase in IFP corresponds to 121.15 bps ($s.e.$=43.12) higher local ETH prices. The local cryptocurrency prices tend to be relatively higher in episodes when more searches about institutional failures. To mitigate the influence of global shocks on the local IFP, we include the currency and weekly fixed effect in the baseline regression. Our findings reveal that a one standard deviation increase in IFP leads to a significant increase of 121.753 bps ($s.e.$=67.16) and 175.050 bps ($s.e.$=80.51) in local BTC and ETH prices, respectively.[40]

We run four sets of robustness checks. First, we control other important time-varying country-level features, including GDP per capita growth, credit by private sector, inflation, the rule of law, government efficiency, corruption scores, and log weekly exchange rate return of the local fiat currency. Table A.8 reports the results of this robustness check. The inflation rate takes β down the most, from 179.002 (s.e.=68.183) to 113.700 (s.e.=47.518) for Bitcoin and from 121.147(s.e.=43.121) to 94.104 (s.e.=39.721) for Ethereum. The magnitude and statistical significance of β remain unchanged after controlling for the other six features.[41] Second, we add the cryptocurrency returns in the past eight weeks to our baseline regression in Table A.10 column (2). Consistent with Makarov and Schoar (2020), the price deviations increase when cryptocurrency prices appreciate; however, the coefficients of IFP almost do not change much: from 179.00 bps ($s.e.$=68.18) to 172.60 bps ($s.e.$=68.33) for Bitcoin, and from 121.15 bps ($s.e.$=43.12) to 111.52 bps ($s.e.$=47.10) for Ethereum.[42] Third, our cryptocurrency price deviations are endogenous to the exchange rate currency return, which might affect the price deviation as the exchange rate is crucial for constructing price deviations. Table A.10 columns (3) and (4) report robustness check results when controlling cryptocurrency returns. The coefficients and significance also remain quite similar: 179.38 bps ($s.e.$=68.12) after controlling for the exchange rate index and 160.52 bps ($s.e.$=55.24)

[40] As searching for the same queries for Google search trends does not always yield the same results, we use the Google search trends downloaded on October 30, 2023, three years after we downloaded the data used in the baseline regression, to run the same regression again. The results still hold, implying that the change in the query results will not significantly affect our results.

[41] We present the robustness results in Table A.9, where we allow for currency and week fixed effects. The findings show consistent patterns, with the magnitude and statistical significance of β_1 largely unchanged.

[42] In Table A.11, we control cryptocurrency return in regressions of Google search indices of "conflict," "crisis," "instability," and "scandal." Institutional failures still predict a surge in price deviation. The coefficients are smaller as a cryptocurrency price rally also partially explains the domestic interest in cryptocurrency.

after controlling for simultaneous currency returns for Bitcoin; 121.12 bps ($s.e.$=43.08) after controlling for the exchange rate index and 119.22 bps ($s.e.$=42.17) after controlling for simultaneous currency returns for Ethereum. These results indicate that our findings of IFP are orthogonal to crypto and currency returns.[43] In the fourth robustness check, we use the price deviation from the crypto prices quoted in euros and replicate the same set of specifications. As shown in Table A.12, the coefficients are similar to our baseline results, indicating that U.S. cryptocurrency dollar price movements do not drive our results. We also further explore the limit of arbitrage across fiat-crypto trading in Section 6.6.

How persistent is the price deviation response? Figure 5 plots the IFP coefficients β_k of predicting price deviations in the next 30 weeks by estimating the following regression:

$$Deviation_{c,t+k} = \alpha + \beta_k IFP_{c,t} + \epsilon_{c,t}$$

The coefficients gradually decay over time and decline to zero in the next 20 weeks. Thus, the IFP impacts tend to be transitory, and arbitrageurs can slowly synchronize the local crypto prices with the international prices. We further discuss the limits of arbitrage in Appendix C and D, and these frictions prohibit local crypto prices from equalizing with the international U.S. dollar price upon the arrival of distrust events.

To explore the economic mechanism, we further document that attention to Bitcoin and Ethereum in Google Trends rises when the IFP index is higher in Table 3. We construct $\Delta GT\_Bitcoin_t = \frac{8 \times GT\_Bitcoin_t}{\sum_{i=1}^{i=8} GT\_Bitcoin_{t-i}}$ and $\Delta GT\_Ethereum_t = \frac{8 \times GT\_Ethereum_t}{\sum_{i=1}^{i=8} GT\_Ethereum_{t-i}}$ as the number of Google searches relative to the past eight-week average. Column (1) shows that if the IFP index increases by one standard deviation, the Bitcoin and Ethereum Google searches would increase by 7.7% ($s.e.$=2.3%) and 17.3% ($s.e.$=4.4%), respectively. Columns (2) - (5) report consistent results that attention to cryptocurrency is also greater when local people search for these four keywords in a higher volume.[44,45] This is consistent with our model

[43]In Column (5), the coefficients are 155.48 bps ($s.e.$=55.44) for BTC and 111.65 bps ($s.e.$=46.37) for ETH after controlling for both crypto and currency returns.

[44]In Table A.13, we add Bitcoin and currency return to regressions. Institutional failures still predict a surge in "Bitcoin" Google searches by 6.0% ($s.e.$=1.5%) and 10.3% ($s.e.$=3.6%). The coefficients are smaller as a cryptocurrency price rally also partially explains the domestic interest in Bitcoin.

[45]Table A.14 reports the results for Google searches on "gold," and we find no evidence that IFP triggers higher search volumes about "gold".

that people start to search for cryptocurrencies when domestic institutional failures hit.

5.3 Price Response Heterogeneity and Distrust

To test Prediction 2, we further 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 all 31 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 4, Columns (2) - (4) report our baseline regressions from Eq.(2) by country trust category. A one-standard-deviation increase in IFP predicts a Bitcoin price deviation increase of 304.81 bps ($s.e.$=160.80) in low-trust countries and of 242.712 bps ($s.e.$=132.32) in medium-trust countries but will have no impact in high-trust countries (31.02 bps ($s.e$=35.82)). This pattern is similar to Ethereum — a one-standard-deviation increase in IFP corresponds to the Ethereum price deviation increases of 196.65 bps ($s.e.$=73.71), 203.42 bps ($s.e.$=77.52), and 3.96 bps ($s.e.$=35.89) in low-trust, medium-trust, and high-trust countries, respectively. In Column (5), we include the interaction term of IFP and $Distrust$ and run the following regression:

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

The coefficient β_2 is 427.31 ($s.e$=201.94) for Bitcoin and 228.49 ($s.e$=126.71) for Ethereum, implying that price responses are stronger in low-trust countries. Investor countries with lower trust levels are prone to chase cryptocurrencies more when concerns about institutions are exacerbated. Table A.15 presents the results for the cumulative Google search indices on the four keywords ("conflict," "crisis," "instability," and "scandal"), which show that the price responses are more pronounced in low-trust countries, particularly for "conflict" and "crisis."[46]

[46] Table A.16 shows the robustness check results with the price deviations from the EUR crypto price; the

Trust may correlate with other country features (e.g., Zak and Knack (2001)). We horse-race distrust with other vital aspects ($Feature_{c,y}$) of a country, including GDP per capita, credit by the financial sector, the rule of law, government effectiveness, and corruption scores.[47] Table 5 reports the horse-racing regressions:

$$Deviation_{c,t} = \beta_1 IFP_{c,t} + \beta_2 Distrust_c \times IFP_{c,t} + \beta_3 Feature_{c,y} \times IFP_{c,t} + \gamma_c + \epsilon_{c,t}$$

Column (1) reports the result of the original specification (as in Table 4, Column (5)), and Columns (2) - (8) show the horse-race results with the five country features. The inflation rate takes β_2 for Bitcoin down the most, from 427.31 ($s.e.$=201.94) to 259.57 ($s.e.$=118.43) while the WGI corruption control score reduces β_2 for Ethereum the most, from 228.49 ($s.e.$=126.71) to 150.55 ($s.e.$=155.22). The β_2's magnitude and statistical significance remain mostly unchanged when we control these seven features, and we find that β_3 is never economically meaningful. The horse-race regressions confirm that distrust delivers unique explanatory power and cannot be easily overruled.[48]

Lastly, we gauge the explanatory power of IFP in price deviation for each country and correlate the explanatory power with the trust level. To make countries comparable, we scale price deviations to a "mean zero, standard deviation one" distribution $\widehat{Deviation}_{c,t}$ for each country-cryptocurrency[49] in this analysis, and we proxy IFP's explanatory power with the country-specific β_c and R-squared (pooling Bitcoin and Ethereum observations together) in the following regression:

$$\widehat{Deviation}_{c,t} = \beta_c IFP_{c,t} + \gamma + \epsilon_{c,t}$$

Figure A.13 Panel A plots the β_c against each country's trust level, and we can see a clear negative relationship with slope -0.42 ($s.e.$=0.17). A one-standard-deviation change in

results are consistent.

[47] 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.

[48] Table A.17 shows the robustness check with price deviations from EUR crypto price.

[49] The normalized price deviation is the raw deviation minus the country-level average and divided by the variance of price deviation, that is, $\widehat{Deviation}_{c,t} = \frac{Deviation_{c,t} - \overline{Deviation_c}}{Var(Deviation_c)}$.

IFP is expected to induce a 0.5-standard-deviation move of the price deviation in a country with the lowest trust level (about -0.5). For a country with the highest trust level (about 0.5), the IFP score is expected to be uncorrelated with the price deviation changes.

We also find a robust negative relationship with slope -7.39 (*s.e.*=3.50) between the R-squared and the trust level. IFP provides the highest explanatory power in Argentina and Mexico, with an R-squared of over 20%. As shown in Figure A.14 and A.15, Argentina and Mexico also report high perceived corruption and a lack of confidence in civil service and governments. News of institutional failure news is a more powerful predictor of cryptocurrency price deviation in countries where people have a worse perceived institutional quality.

6 Discussion

This section validates the data validity of the trust and the institutional failure probability (IFP) index. Then, we investigate and try to rule out alternative explanations related to trading volume, exchange rates, and capital controls for our IFP predictability in price deviations. Lastly, we discuss the segmented cryptocurrency market and arbitrage frictions that enable price deviations to persist.

6.1 Economic Foundations of Distrust

First, we document that our distrust measure captures the lack of confidence in local institutions. We correlate GPS trust with measures of confidence in institutions and perceived corruption in various organizations from the World Value Survey (WVS henceforth).[50] WVS elicits respondents' confidence levels in banks, major companies, government, politics, and civil service and reports the percentage of respondents in each category by confidence level. We assign a score of 2 to "A great deal of confidence," 1 to "Quite a lot of confidence," -1 to "Not very much confidence," -2 to "None at all," and 0 to "Don't know" or "No answer."

[50] WVS runs seven waves of its survey. The countries covered in each wave are slightly different. Our analysis prioritizes the data from the latest wave (Wave 7). For the countries not covered by Wave 7, we use the data from Wave 6, and so on. 17 countries in our sample can be found in WVS. GPS provides a much more extensive country coverage than WVS.

The country-specific confidence score is the weighted average (multiplied by 100) of all survey respondents in the country. The scale of the score ranges from -200 to 200. Similarly, WVS surveys perceived corruption in business, civil service, and local and state governments. We assign a score of 2 to "None of them," 1 to "Few of them," -1 to "Most of them," -2 to "All of them," and 0 to "Don't know" or "No answer.", and we can calculate the corruption control score accordingly.

Trust is positively correlated with confidence in institutions. Figure A.14 and Table A.18 show that a one-unit increase in GPS trust predicts 112.70 points ($s.e.$ = 47.01) more confidence in banks, 50.83 ($s.e.$ = 24.18) for companies, 128.08 ($s.e.$ = 41.99) for government, 108.1 ($s.e.$ = 41.72) for politics, 117.0 ($s.e.$ = 31.67) for civil service, and 119.25 ($s.e.$ = 38.35) for justice.

People in nations with higher distrust also believe that corruption is more common. Figure A.15 and Table A.18 report the relationship between trust and the perceived control of corruption in business, civil service, and local and state government. Trust corresponds to a lower perception of corruption: the regression coefficient of perceived corruption on trust is 65.17 ($s.e.$ = 30.37) for business corruption, 85.10 ($s.e.$ = 39.00) for corruption in civil services, 100.87 ($s.e.$ = 44.85) for national/state government corruption, and 69.73 ($s.e.$ =36.37) for local government corruption, respectively.[51]

6.2 Institutional Failure Index Validation

One concern is that the institution failure index (IFP) might capture some global shocks. We calculate the global institution failure index as the average IFP of all 31 countries. We

[51] As Falk et al. (2018) confirms that the 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 provides questions regarding general trust in most people, in people you know personally, in your neighbor, and in people you first meet. As before, we assign the weight of 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.18 shows that a one-unit increase in the GPS trust measure corresponds to 20.92 ($s.e.$ = 10.42) higher score of the questions "most people can be trust", 67.13 ($s.e.$ = 34.24) higher trust to people you know personally, 60.38 ($s.e.$ = 26.10) higher trust in neighbor, and 46.24 ($s.e.$= 30.65) higher trust in people you first met, respectively. The R-squared values of the above regressions are 13.43%, 15.47%, 20.31%, and 9.78% for these four trust questions. These results confirm that the trust measures in GPS and VWS are broadly consistent, and GPS provides better country coverage.

define the Adjusted Institutional Failure Index ($Adj\_IFP_{c,t}$) as the difference between the local IFP and the global IFP. Table A.19 indicates that a one-standard-deviation increase in adjusted IFP predicts a price deviation of 58.86 bps ($s.e.$ = 24.46) and 61.54 bps ($s.e.$ = 20.67) for BTC and ETH, respectively. Our main findings are unlikely to be driven by global shocks.

Yu and Zhang (2022) argues that investors buy cryptocurrency as a "safe haven asset" when the local Economic Policy Uncertainty (EPU) Index is high. We test whether the IFP captures a similar policy uncertainty as the EPU.[52] First, we perform pairwise correlations between the IFP and the EPU in 15 countries and generate a correlation histogram in Figure A.16. The IFP and EPU are modestly negatively correlated at -8.36% with a t-value of -0.838 rather than a positive correlation. Many institutional failure events, such as corruption, do not necessarily add to the local policy uncertainty. For example, we identify the Panama tax-avoidance scandal of David Cameron, the former prime minister of the United Kingdom, driving an IFP peak. Figure A.17 illustrates that following the scandal on April 3rd, 2016, both the BTC price deviations and IFP increased while the EPU dropped during the event outbreak.

Next, we validate whether EPU statistically explains the IFP's predictability in price deviations by including EPU as a control variable in the baseline specification and report the results in Table A.20. After accounting for the EPU index, the coefficient of IFP for BTC increases from 138.09 ($s.e.$ = 47.18) to 141.54 ($s.e.$ = 46.80), while for ETH, it increases from 63.54 ($s.e.$ = 41.51) to 68.25 ($s.e.$ = 41.53). These results suggest that IFP captures a different driving force of cryptocurrency price deviations from the EPU.

6.3 Trading Volume

Is it possible that a liquidity shortage might drive up local cryptocurrency prices? As the crypto trading volume rises over time, we use the following two metrics to scale the trading volume. First, we compute volume share as the percentage of trading volume in the local country as a percentage of the global total trading volume. Second, we define volume growth

[52]EPU index is proportional to the share of newspaper articles that discuss economic policy uncertainty.

as the ratio of raw volume to the past eight-week average trading volume.

We first revisit the event studies. Figures A.18 and A.19 plot the event study on Bitcoin and Ethereum's volume share and growth for political events and government-related socioeconomic events, respectively. In all of the figures, we do not observe any drop in trading volume in either the level or growth rate. Table A.21 reports the pre and post-changes in trading volume: the Bitcoin volume share is only 3% ($s.e.$=3%), and volume growth is 8.9% ($s.e.$=5.1%) higher. We also find a modest increase by 0.1% ($s.e.$=0.01%) in the volume share of Ethereum upon government-related socioeconomic events.[53]

Next, we investigate trading volume in the panel data. In Table A.22, we report the effect of the IFP and Google Search Index on ΔVol and Vol_Share. Most of the coefficients are positive but not statistically significant, which means that IFP is modestly positively correlated with the trading volume of cryptocurrencies. Then, we also control the ΔVol and Vol_Share in the Eq.2 and report the regression results in Table A.23. The results show that the coefficients would not change significantly when we control the volume compared with Table 2.

Next, we replicate our baseline results conditional on the trading volume and check whether our results are driven by low liquidity periods. In Table A.24, we experiment with subsamples with weeks with positive volume (not zero or missing values) reported in Column (2), weeks with trading volume above the 25^{th} percentile in Column (3), weeks with trading volume above the median trading volume in Column (4), and weeks with the largest trading volume above the 75^{th} percentile in Column (5). For Bitcoin, a one-standard-deviation increase in IFP corresponds to 165.88 ($s.e.$=67.27), 193.57($s.e.$=73.13), 111.92($s.e.$=42.31), and 100.54 ($s.e.$=44.28) bps increase in price deviation in these four subsamples respectively. Similarly, for Ethereum, a one-standard-deviation increase in IFP leads to 115.72 ($s.e.$=43.12), 147.34 ($s.e.$=42.05), 140.44 ($s.e.$=34.73), and 94.49 ($s.e.$=41.43) bps increase in price deviation in these four subsamples, respectively. A higher IFP still induces an increase in the price deviation, even in the quartile with the largest trading volume.

[53] For events that do not move the price premium, we also do not find either the volume share or volume growth of Bitcoin and Ethereum.

These results suggest that liquidity shortage is unlikely to fully explain the widening price difference. On the contrary, the volume tends to be higher during periods with more attention to institutional failure. Thus, it is consistent with the mechanism that stronger local Bitcoin demand drives a higher price and trading volume. Moreover, our baseline results (Prediction 1) hold when we control trading volume and different trading volume thresholds. Therefore, liquidity is unlikely to be the driving force for price deviation changes.

6.4 Exchange Rates

The exchange rate is an essential variable for price deviation calculation. This subsection rules out that exchange rate changes drive our findings. We first evaluate whether exchange rate changes affect the price deviation. Figure A.20 plots the coefficients of uni-variate regressions of price deviation on lead and lagged exchange rate returns. We find that one-week lagged and simultaneous currency appreciation contributes to the increase in price deviation: a one-bps increase in the exchange rate translates into a 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 the exchange rate, about 20% passes into price deviation simultaneously and takes about two to three weeks to fade away. The relationship itself demonstrates the limited arbitrage in cryptocurrency trading.

Do exchange rate impacts contaminate our empirical identifications? The short answer is no. We add the currency exchange rate index[54], and simultaneous currency returns to the main specifications in Table A.10. The coefficients do not change much: the Bitcoin price deviations rise by 179.38 bps ($s.e.$=68.12) when we control for simultaneous currency return, 160.52 bps ($s.e.$=55.24) after controlling for the exchange rate and Ethereum price deviations rise by 121.12 bps ($s.e.$=43.08) when we control for simultaneous currency return, 119.22 bps ($s.ez.$=42.17) when we control for the exchange rate. Consistent with Figure A.20, exchange rate returns positively predict the price deviations but are orthogonal to the IFP factor.

[54]The index is the cumulative log currency returns, starting from January 2015. The index measures the relative exchange rates in our sample period.

We further explore whether Bitcoin price deviations can predict potential depreciation in the currency markets, e.g., investors might want to build a Bitcoin position to hedge the future currency depreciation risk in the home country. First, we relate Bitcoin price deviations to the covered interest parity (CIP) deviations (Du et al. (2018)). Table A.25, Column (1) reports the univariate regression but does not identify any relationship with CIP deviations. In Columns (2)-(5), we check whether Bitcoin price deviations predict currency depreciation or appreciation. We also find no evidence that Bitcoin price deviations predict anything in the future one week, eight weeks, or 24 weeks. Moreover, a high-rise price deviation does not indicate a higher probability of a fiat currency crisis, defined as a 15% depreciation in the following 24 weeks. Our results imply that Bitcoin price deviations mostly come from the factors determining Bitcoin demand but contain little information on FX markets.

6.5 Roles of Capital Controls

Many barriers can arise in this procedure and prevent arbitragers from acting. It is often argued in the literature that capital controls are the primary reason for price deviations across countries.[55] This section investigates the role of capital control in driving price deviation responses to IFP.

One concrete example is Argentina. Since September 2019, Argentine companies have been subject to a central bank rule that requires them to repatriate all export earnings and convert them into pesos at the official exchange rate set by the central bank. Further, companies must obtain central bank approval to access U.S. dollars. Simultaneously, as shown in Figure A.1, the Argentine Bitcoin price surged to 40% more expensive than the U.S. dollar price when the central bank tightened the capital controls in Argentina.

Under tightened 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

[55]See, e.g., Makarov and Schoar (2019) Makarov and Schoar (2020), Yu and Zhang (2022), Choi et al. (2022)

by Chinn and Ito (2006), in which they construct an index measuring a country's degree of capital account openness. It is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Table 6 reports the analysis of capital control change (annually updated capital openness index) and cryptocurrency price deviations. A one-unit increase in capital closeness corresponds with 653.387 and 337.518 bps in the price deviations of Bitcoin and Ethereum, respectively. Controlling IFP, we can see from Column (6) that capital closeness has predictive power for the price deviation, with the coefficients remaining primarily unchanged. Our findings confirm that capital control matters for price deviation but does not undermine the importance of IFP. In Column (7), we add the interaction term of IFP and capital controls to the regression and document that price deviation responses to IFP are stronger in countries with tighter capital controls. Therefore, the institutional failure channel that drives price deviation is more pronounced in more constrained countries.

6.6 Market Segmentation and Arbitrage Frictions

In the last step, we dive into the market structure of cryptocurrency trading and document various frictions in the arbitrage across fiat-crypto trading pairs. For example, investors with Swedish Krona typically trade cryptocurrencies through peer-to-peer OTC platforms, such as LocalBitcoins and Bisq.[56] Arbitragers can only sell a tiny number of Bitcoin at a time; for example, the order size per advertisement ranged from 150 to 1,200 SEK on October 8, 2020. Foreign traders encounter difficulties participating in the local cryptocurrency market due to the requirement of a local bank account for trading on the local peer-to-peer OTC platform.

Cross-currency arbitrage can be costly even in countries with exchanges that facilitate trading. Korea has six active cryptocurrency exchanges: Huobi Korea, GOPAX, Korbit, Coinone, UPbit, and Bithumb Korea. However, all these exchanges only have active trading

[56] OTC platforms allow users to post the quantity and quote in any fiat currency without a market-making system. Thus, these OTC markets tend to provide many fiat-crypto trading pairs, although liquidity is limited.

in Korean Won—almost no investors buy or sell cryptocurrency with the U.S. dollar. Arbitragers need to send Bitcoins from a US crypto exchange to a Korean exchange and typically pay various transaction fees: Coinbase charges 1% to withdraw cryptocurrencies on top of trading costs and gas fees.[57,58] Depending on the blockchain network's congestion, sending Bitcoin across addresses typically takes 10-60 minutes to complete. 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, 2020, and only 75 were active with trades. We compute volume share as the number of Bitcoins traded in one currency divided by the total Bitcoins traded on the same exchange. Then, we define the primary trading pair as the currency with the highest volume share. Figure A.21 counts the number of exchanges by the volume share of the primary trading pair. De facto, 37 of the 75 exchanges only transact in one unique currency.

Trading volume depletes if we look beyond the primary currency used in the exchange. Figure A.22 summarizes the average volume share of the top 5 active trading pairs. The primary currency accounts for 87.9% of the total volume. The number rapidly drops to 8.8% for the second functional crypto-fiat trading pair, 2.2% for the third, 0.8% for the fourth, and 0.3% for the fifth. It is challenging to implement arbitrage across currencies within one exchange.

7 Conclusion

This paper suggests that distrust toward domestic politics or economic situations drives up the local cryptocurrency price premium relative to the prevalent dollar price. The premium response is notably more prominent in low-trust countries than in high-trust countries. Domestic demand for cryptocurrency likely drives these widened price deviations, as people search for "Bitcoin" and "Ethereum" more than usual on Google when the IFP index is high. Market segmentation and capital controls are both necessary for the phenomena to exist.

[57]See: https://www.binance.com/en/fee/depositFee

[58]See: https://help.coinbase.com/en/coinbase/trading-and-funding/pricing-and-fees/fees

The price deviation responses are also stronger when the country imposes tighter capital controls.

Our findings suggest that the fundamental value of cryptocurrency, at least partially, contributes to the distrust of local governments. The peer-to-peer blockchain network becomes more attractive to domestic investors, particularly when the country's fragile domestic financial system and corrupt politics become more salient to the public, or the government tries to limit financial freedom. Cryptocurrency can weaken capital controls and other domestic government exploitation as investors can always store their wealth in cryptocurrencies.

References

Abadi, Joseph, and Markus Brunnermeier, 2018, Blockchain economics, Working Paper 25407, National Bureau of Economic Research.

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

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

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.

Borri, Nicola, and Kirill Shakhnov, 2022, The cross-section of cryptocurrency returns, *The Review of Asset Pricing Studies* 12, 667–705.

Borri, Nicola, and Kirill Shakhnov, 2023, Cryptomarket discounts, *Journal of International Money and Finance* 139, 102963.

Brauneis, Alexander, Roland Mestel, Ryan Riordan, and Erik Theissen, 2018, Bitcoin exchange rates: How integrated are markets?, *Available at SSRN 3249477* .

Budish, Eric, 2018, The economic limits of bitcoin and the blockchain, Working Paper 24717, National Bureau of Economic Research.

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

Carlson, Jill, 2016, Cryptocurrency and capital controls, *Available at SSRN 3046954* .

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

Chinn, Menzie D, and Hiro Ito, 2006, What matters for financial development? capital controls, institutions, and interactions, *Journal of Development Economics* 81, 163–192.

Choi, Kyoung Jin, Alfred Lehar, and Ryan Stauffer, 2022, 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, 2023, Crypto wash trading, *Management Science* 69, 6427–6454.

Cong, Lin William, Ye Li, and Neng Wang, 2021, Tokenomics: Dynamic adoption and valuation, *The Review of Financial Studies* 34, 1105–1155.

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.

Eom, Yunsung, 2021, Kimchi premium and speculative trading in bitcoin, *Finance Research Letters* 38, 101505.

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, 2022, Corporate capture of blockchain governance, *The Review of Financial Studies* .

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, 2022, Trust and insurance contracts, *The Review of Financial Studies* 35, 5287–5333.

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

Goswami, Gour Gobinda, and Tapas Kumar Saha, 2022, Fourier nonlinear quantile unit root test of purchasing power parity in cryptocurrencies, *Applied Economics Letters* 1–11.

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).

Hu, Maggie, Adrian D Lee, and Tālis J Putniņš, 2021, Evading capital controls via cryptocurrencies: Evidence from the blockchain, *Available at SSRN 3956933* .

Huang, Guan-Ying, Yin-Feng Gau, and Zhen-Xing Wu, 2022, Price discovery in fiat currency and cryptocurrency markets, *Finance Research Letters* 47, 102615.

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

Kristoufek, Ladislav, and Elie Bouri, 2023, Exploring sources of statistical arbitrage opportunities among bitcoin exchanges, *Finance Research Letters* 51, 103332.

Krückeberg, Sinan, and Peter Scholz, 2020, Decentralized efficiency? arbitrage in bitcoin markets, *Research in International Business and Finance* 76, 135–152.

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

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.

Nguyen, Thai Vu Hong, Binh Thanh Nguyen, Kien Son Nguyen, and Huy Pham, 2019, Asymmetric monetary policy effects on cryptocurrency markets, *Research in International Business and Finance* 48, 335–339.

Reynolds, Julia, Leopold Sögner, and Martin Wagner, 2021, Deviations from triangular arbitrage parity in foreign exchange and bitcoin markets, *Central European Journal of Economic Modelling and Econometrics* 105–146.

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.

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.

Shu, Ao, Feiyang Cheng, Jianlei Han, Zini Liang, and Zheyao Pan, 2023, Arbitrage across different bitcoin exchange venues: Perspectives from investor base and market related events, *Accounting Finance* .

Shynkevich, Andrei, 2021, Bitcoin arbitrage, *Finance Research Letters* 40, 101698.

Sockin, Michael, and Wei Xiong, 2023, A model of cryptocurrencies, *Management Science* 69, 6684–6707.

Williams, Michael, Mucahit Kochan, and David Green, 2022, The impact of chinese capital outflows on bitcoin vs. yuan relationships: A multi-period analysis, *Journal of Finance Issues* 20, 53–69.

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

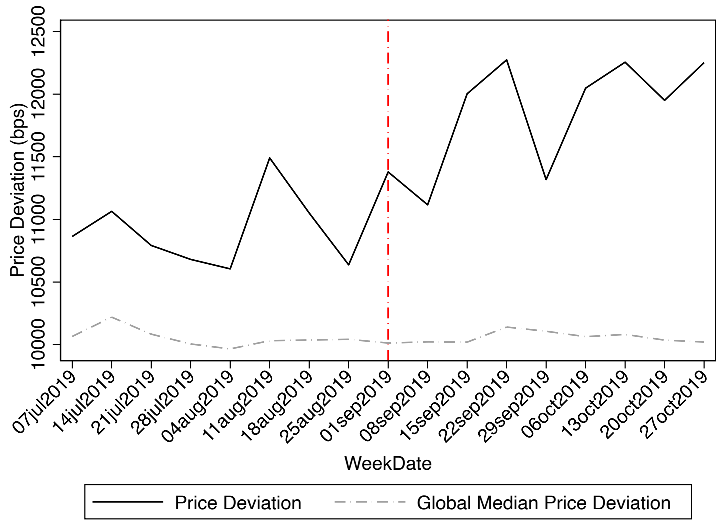
You, Yang, and Kenneth S Rogoff, 2022, Redeemable platform currencies, *The Review of Economic Studies* .

Yu, Yang Gloria, and Jinyuan Zhang, 2022, Flight to bitcoin, *Available at SSRN 3278469* .

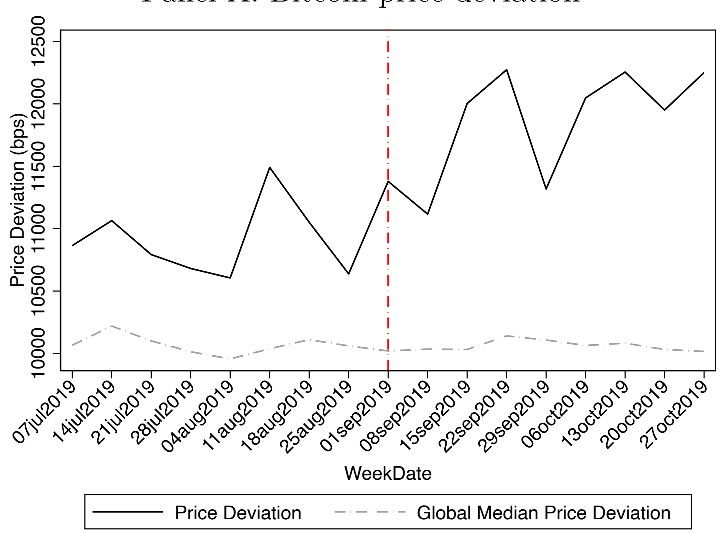
Zak, Paul J, and Stephen Knack, 2001, Trust and growth, *The Economic Journal* 111, 295–321.

Figures and Tables

Figure 1: Argentina's monetary crisis and additional capital control



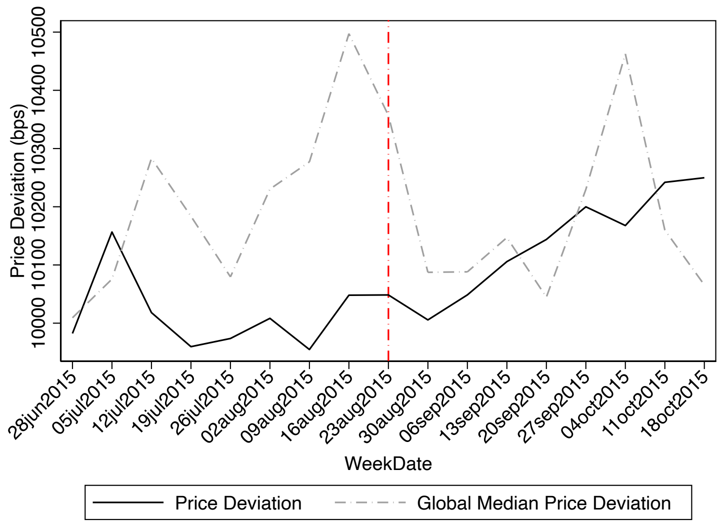
Panel A: Bitcoin price deviation



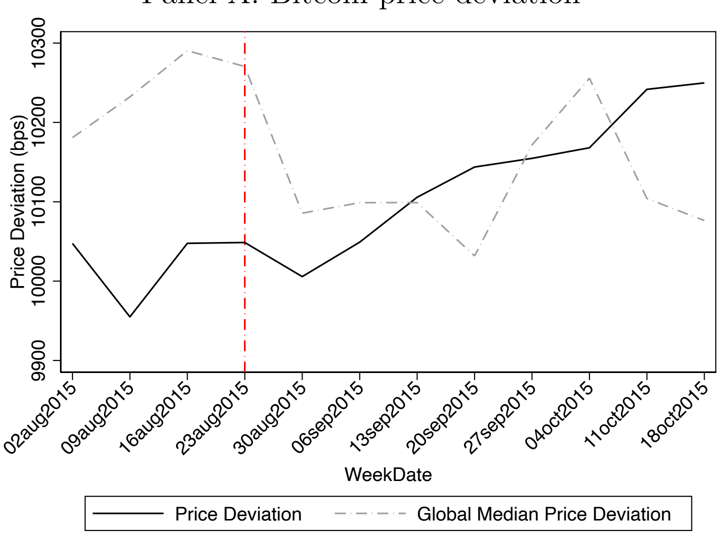
Panel B: Ethereum price deviation

Notes: The figure plots the Bitcoin and Ethereum price deviations around September 1, 2019, when the Argentina government imposed new capital controls to combat the Peso depreciation crisis. Panel A plots the Bitcoin price deviations from June 7 to October 27, 2019 (16 weeks around the event date). Panel B plots the Ethereum price deviations in the same time window.

Figure 2: The 2015 China stock market crash



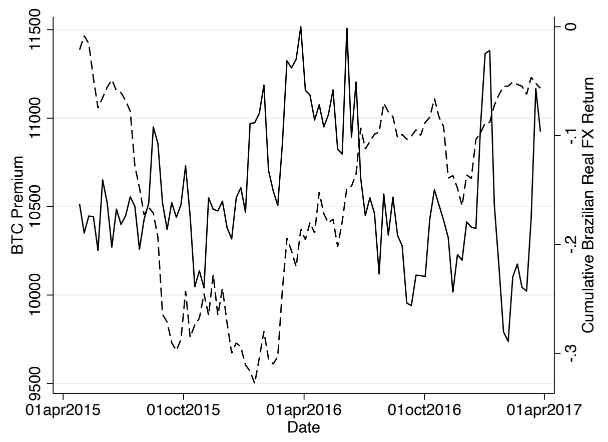
Panel A: Bitcoin price deviation



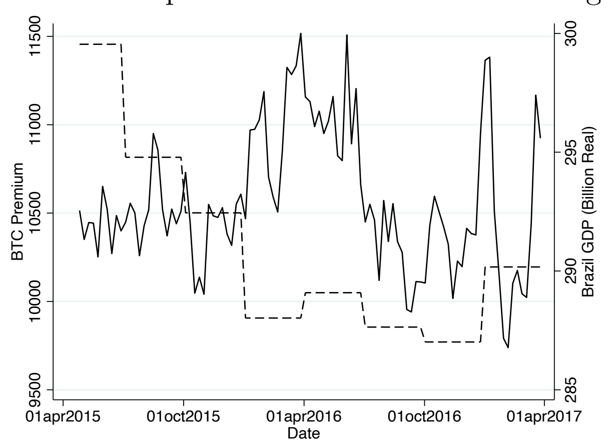
Panel B: Ethereum price deviation

Notes: The figure shows the Bitcoin and Ethereum price deviation around August 23, 2015, the biggest one-day loss in the Chinese stock market crash. Panel A plots the Bitcoin price deviations from June 28 to October 18, 2015 (16 weeks around the event date). Panel B plots the Ethereum price deviations from August 2 to October 18, 2015, as the Ethereum price data begin from August 2, 2015. There are only four-week price data before August 23, 2015.

Figure 3: Brazil's economic recession



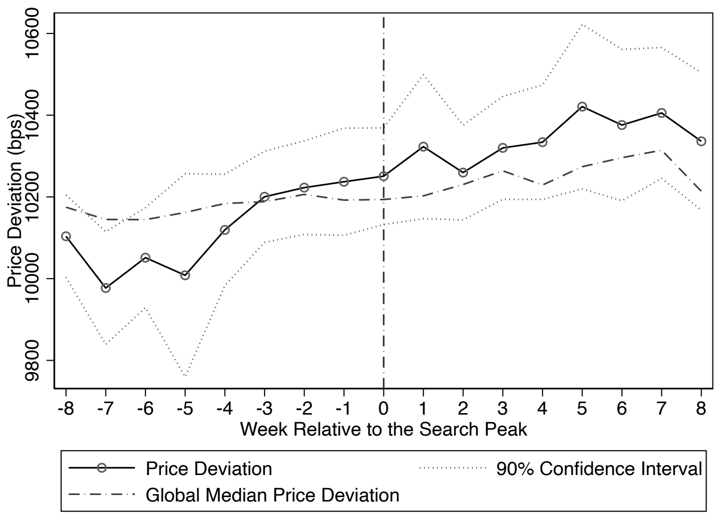
Panel A: Bitcoin price deviation and the exchange rate



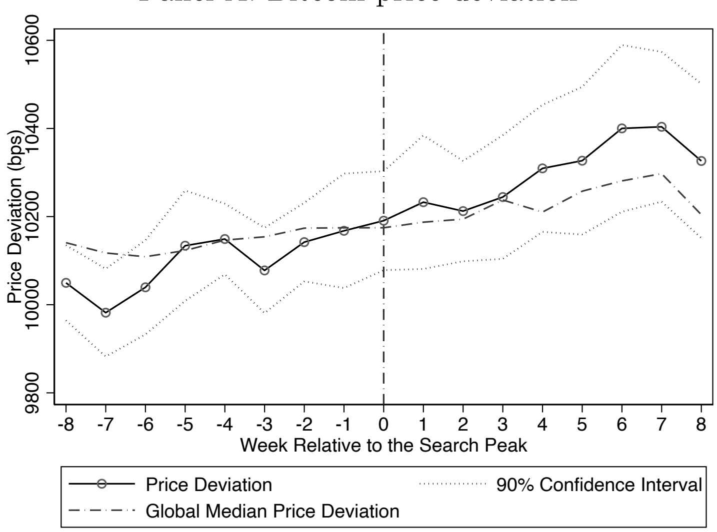
Panel B: Bitcoin price deviation and Brazilian GDP

Notes: This figure plots the time-series relationship between Bitcoin price deviations, the Brazilian Real exchange rate, and Brazil's GDP. In Panel A, the solid line is the BTC price deviation, and the dashed line is the normalized exchange rate. The exchange rate index was normalized to zero on April 1, 2015, and each point represents the cumulative currency returns since April 2015. In Panel B, the solid line is the BTC price deviation, and the dashed line represents Brazil's quarterly GDP in the current U.S. dollar.

Figure 4: Event studies: price deviations around political scandals



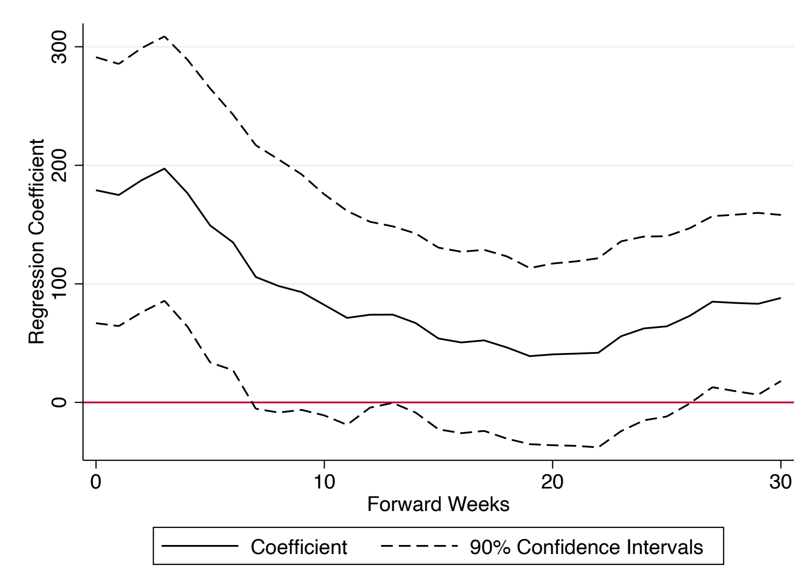
Panel A: Bitcoin price deviation



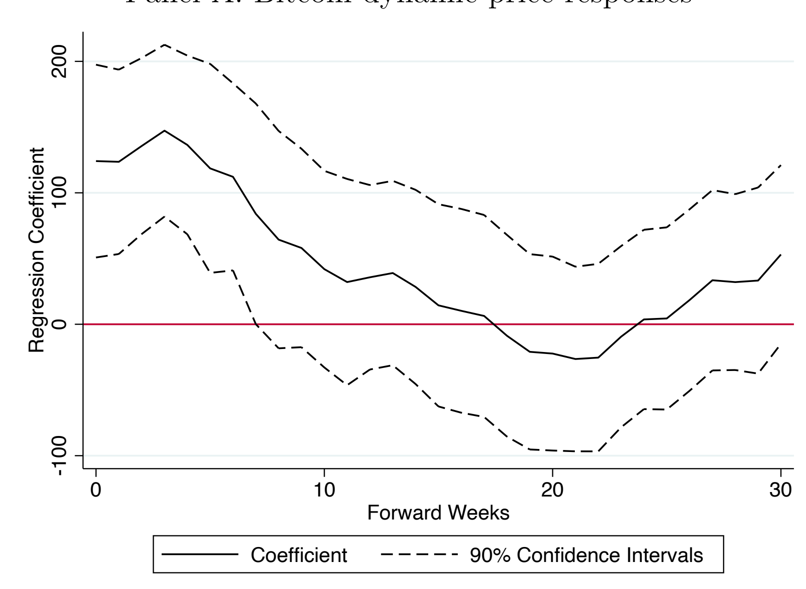
Panel B: Ethereum Price Deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 43 political events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the average global median price deviations of the 31 countries in the same event window. Panel A plots the Bitcoin price deviations, and Panel B plots the Ethereum price deviations.

Figure 5: Dynamic price responses to the institutional failure index



Panel A: Bitcoin dynamic price responses



Panel B: Ethereum dynamic price responses

Notes: This figure plots the dynamic responses β_k of cryptocurrency price deviations to the institutional failure probability index (IFP) by estimating the following panel regressions with price deviations in the next 30 weeks:

$$Deviation_{c,t+k} = \alpha + \beta_k IFP_{c,t} + \epsilon_{c,t}$$

The first data point β_0 is our baseline panel regression coefficient in Table 2, Column (1). Panel A plots the dynamic coefficients of Bitcoin price deviations, and Panel B plots the dynamic coefficients of Ethereum price deviations.

Table 1: Event studies on the price deviation

This table reports the pre and post-changes in price deviation for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Bitcoin price deviation minus the global market median deviation. In Panel C, the dependent variable is the Ethereum price deviation. In Panel D, the dependent variable is the Ethereum price deviation minus the global market median deviation. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
	Panel A: Dependent Variable $Deviation_{BTC}$				
Post	199.858***	216.371**	-141.209	11.329	91.466
	(56.452)	(70.311)	(105.190)	(66.035)	(105.084)
	Panel B: Dependent Variable $Adjusted\_Deviation_{BTC}$				
Post	137.054***	102.347	-146.197	-14.081	-7.897
	(41.429)	(65.735)	(92.326)	(62.878)	(103.693)
# events	43	5	6	17	17
	Panel C: Dependent Variable $Deviation_{ETH}$				
Post	177.571***	236.393*	17.407	8.088	24.591
	(50.961)	(85.508)	(25.353)	(61.554)	(79.483)
	Panel D: Dependent Variable $Adjusted\_Deviation_{ETH}$				
Post	101.353***	90.353	-136.385	-11.021	-77.599
	(33.028)	(91.411)	(159.152)	(66.918)	(69.006)
# events	41	4	4	15	17

Table 2: Price deviation responses to the institutional failure

This table reports panel regressions of the cryptocurrency price deviation on the institutional failure probability index (IFP) in Columns (1)-(3) and cumulative Google Trends for "conflict" in Column (4), "crisis" in Column (5), "instability" in Column (6), and "scandal" in Column (7) by estimating the following regressions:

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

where $GT_{c,t}$ denotes the IFP and cumulative Google Trends indices. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. Both country and week fixed effects are included in Column (2). In Column (3), the countries with tight capital control are excluded from the sample. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$						
	(1) IFP	(2) IFP	(3) IFP	(4) Conflict	(5) Crisis	(6) Instability	(7) Scandal
Google Trends	179.002**	121.753*	133.813**	149.784**	67.093**	125.198**	87.498**
	(68.183)	(67.161)	(54.843)	(64.665)	(32.260)	(60.412)	(39.698)
Currency FE	YES	YES	YES	YES	YES	YES	YES
Week FE	NO	YES	NO	NO	NO	NO	NO
# observation	7,688	7,688	6,200	7,688	7,688	7,688	7,688
	Panel C: Dependent Variable $Deviation_{ETH}$						
Google Trends	121.147***	175.050**	105.188**	91.077**	33.990	120.156*	-19.781
	(43.121)	(80.512)	(44.719)	(43.503)	(27.420)	(68.427)	(60.913)
Currency FE	YES	YES	YES	YES	YES	YES	YES
Week FE	NO	YES	NO	NO	NO	NO	NO
# observation	6,943	6,943	5,598	6,943	6,943	6,943	6,943

Table 3: Institutional failures and attention to cryptocurrency

This table reports the impact of institutional failures on attention to cryptocurrencies. In Panel A, the dependent variable is the growth of "bitcoin" Google Trends index $\Delta GT\_Bitcoin_t = \frac{8 \times GT\_Bitcoin_t}{\sum_{i=1}^{i=8} GT\_Bitcoin_{t-i}}$. In Panel B, the dependent variable is the growth in "Ethereum" Google searches $\Delta GT\_Ethereum_t = \frac{8 \times GT\_Ethereum_t}{\sum_{i=1}^{i=8} GT\_Ethereum_{t-i}}$. The independent variable is the institutional failure probability index (IFP) in Column (1) and cumulative Google Trends for "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5).

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

where $GT_{c,t}$ denotes the IFP and cumulative Google Trends indices. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $\Delta GT\_Bitcoin$				
	(1) IFP	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	0.077***	0.065***	0.062***	0.035**	0.017
	(0.023)	(3.064)	(3.045)	(2.089)	(1.211)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $\Delta GT\_Ethereum$				
Google Trends	0.173***	0.165***	0.113***	0.064	0.084***
	(0.044)	(0.042)	(0.033)	(0.045)	(0.025)
# observation	6,943	6,943	6,943	6,943	6,943

Table 4: Heterogeneous price responses by trust

This table reports the heterogeneous price response to the institutional failure probability (IFP) index by the country's trust level from Global Preference Survey (GPS). High-trust countries in Column (2) refer to 11 countries with GPS trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a GPS trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a GPS trust score below -0.1. Column (5) reports the test for heterogeneous response by trust level:

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

where $IFP_{c,t}$ denotes the IFP index. $Distrust_c$ is GPS trust score. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
IFP	179.002**	31.016	242.712	304.812*	-226.601
	(68.183)	(35.819)	(132.321)	(160.795)	(164.464)
$IFP \times Distrust$					427.311**
					(201.943)
# obsercation	7,688	2,728	2,232	2,728	7,688
	PanelB: Dependent Variable $Deviation_{ETH}$				
IFP	121.147***	3.961	203.424**	196.654**	-93.644
	(43.121)	(35.889)	(77.517)	(73.709)	(126.619)
$IFP \times Distrust$					228.488*
					(126.705)
# obsercation	6,943	2,465	1,999	2,479	6,943

Table 5: Horse-racing regressions with other country features

This table reports regressions that horse-race trust with other country features $Feature_{c,y}$: GDP per capita in Column (2), credit by the private sector in Column (3), annual inflation in Column (4), the WGI rule of law index in Column (5), WGI government effectiveness index in Column (6), and WGI corruption control score in Column (7).

$$Deviation_{c,t} = \beta_1 IFP_{c,t} + \beta_2 Distrust_c \times IFP_{c,t} + \beta_3 Feature_{c,y} \times IFP_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $IFP_{c,t}$ denotes the institutional failure probability index. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$						
	(1) N/A	(2) GDP	(3) Credit	(4) Inflation	(5) Law	(6) Gov Eff	(7) Corruption
IFP	-226.601	-511.609	-235.615	-117.784	-277.127	-266.213	-71.256
	(164.464)	(899.795)	(161.775)	(115.679)	(188.057)	(174.342)	(200.686)
$IFP \times Distrust$	427.311**	436.314*	445.419**	259.570**	471.686**	469.739**	340.061**
	(201.943)	(215.008)	(194.979)	(118.427)	(215.214)	(211.149)	(165.781)
$IFP \times Covariate$		10.187	-4.742	1.108	25.141	17.243	-1.160
		(28.888)	(67.908)	(9.117)	(76.637)	(53.407)	(1.423)
# observation	7,688	7,688	7,030	7,441	7,440	7,440	7,440
	Panel B: Dependent Variable $Deviation_{ETH}$						
IFP	-93.644	513.813	-38.285	-54.973	-25.212	-39.064	68.699
	(126.619)	(982.595)	(140.696)	(119.901)	(152.640)	(145.065)	(209.727)
$IFP \times Distrust$	228.488*	213.656	199.152	199.264	195.649	192.075	150.548
	(126.705)	(139.900)	(127.972)	(117.475)	(134.705)	(135.054)	(155.222)
$IFP \times Covariate$		-21.883	-50.744	-8.997	-55.547	-45.759	-0.999
		(32.521)	(38.785)	(15.800)	(46.471)	(33.779)	(0.871)
# observation	6,943	6,943	6,332	6,718	6,717	6,717	6,717

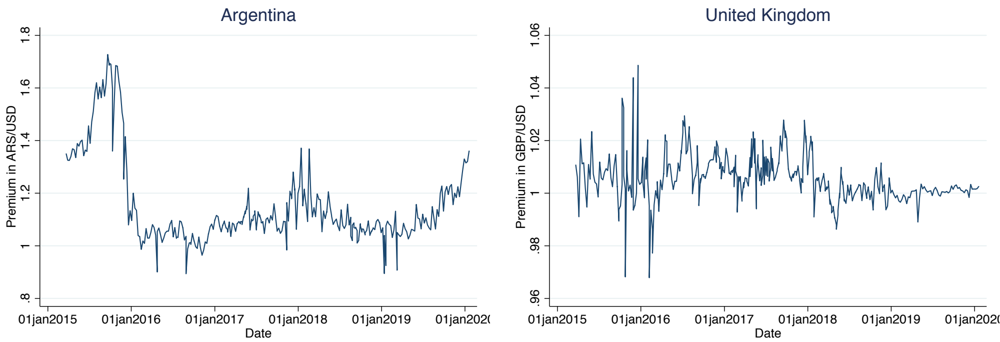
Table 6: Capital controls and price deviation responses

This table reports how capital controls (measured with the annually updated Ito-Chinn capital account openness index) interact with cryptocurrency price responses to the institutional probability failure (IFP) index. The dependent variable is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. Column (1) reports the uni-variate regressions of the price deviation response to the IFP. Column (3) reports the uni-variate regressions of the price deviation response on the capital account closeness index (one minus the Ito-Chinn capital account openness index). Column (5) reports regressions including IFP and capital account closeness. Column (7) reports regressions that add an interaction term of IFP and capital account closeness in addition to the specification in Column (5). We further report regressions that control the year fixed effects in Columns (2), (4), (6), and (8). The country fixed effects are included in all specifications. Robust standard errors are clustered at the currency and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IFP	179.002**	139.890**			155.886***	125.439**	143.718**	113.813**
	(68.183)	(54.702)			(54.726)	(45.922)	(53.222)	(45.878)
$Closeness$			669.315***	653.387***	616.567***	630.877***	626.578***	643.147***
			(6.219)	(54.666)	(5.899)	(45.771)	(25.119)	(59.294)
$IFP \times Closeness$							62.745	65.675
							(73.279)	(65.713)
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
# observation	7,688	7,688	7,688	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$							
IFP	121.147***	156.080**			116.136***	152.928**	102.136***	138.176**
	(43.121)	(65.812)			(41.457)	(65.194)	(35.613)	(57.018)
$Closeness$			282.464***	337.518***	260.210***	324.475***	288.555***	356.870***
			(42.041)	(36.179)	(54.863)	(36.836)	(45.977)	(38.335)
$IFP \times Closeness$							86.751*	94.491**
							(43.396)	(45.572)
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
# observation	6,943	6,943	6,943	6,943	6,943	6,943	6,943	6,943

A Internet Appendix: Figures and Tables

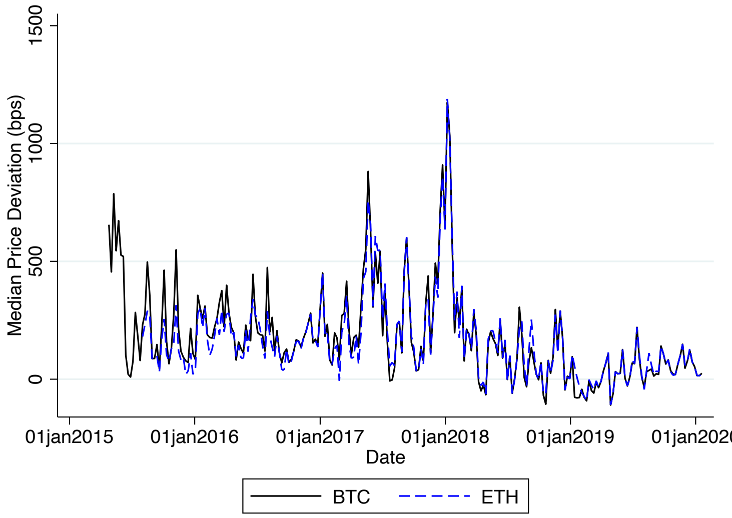
Figure A.1: The price deviations in Argentina and the United Kingdom



Notes: This figure plots the price deviations in Argentina and the United Kingdom from January 2015 to January 2022. The price deviation in the country c is defined as:

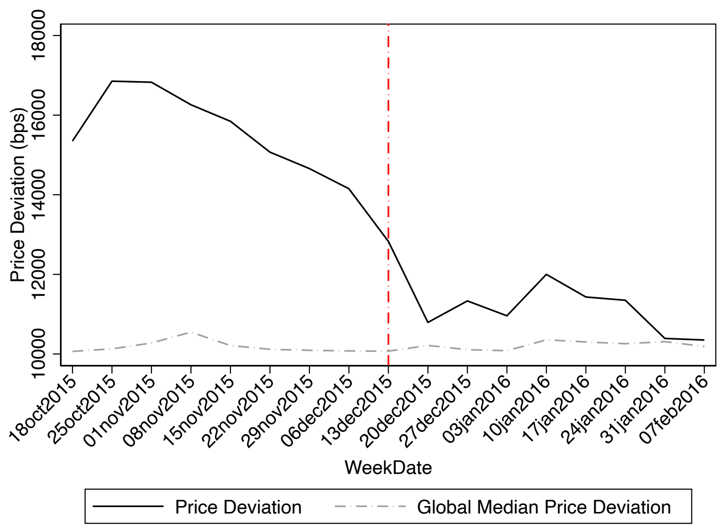
$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}}$$

Figure A.2: The median price deviation of 31 countries over time

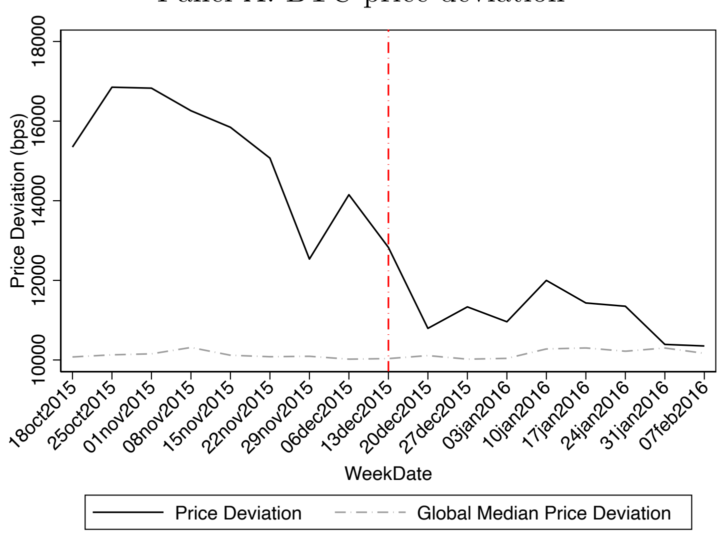


Notes: This figure plots the trend of the median number of price deviations of cryptocurrencies.

Figure A.3: Removal of capital controls in Argentina



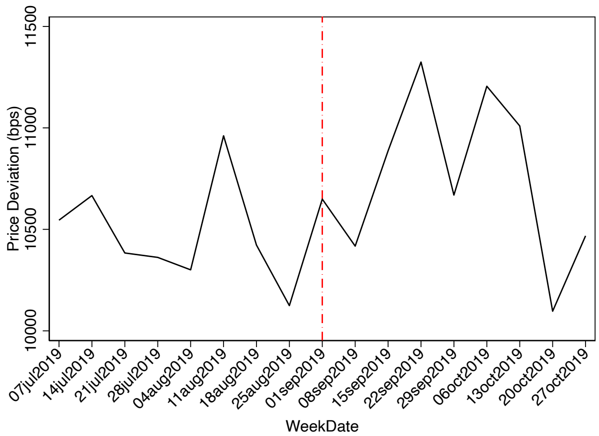
Panel A: BTC price deviation



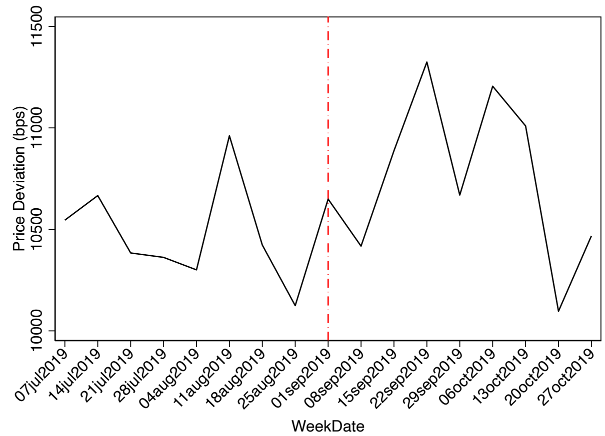
Panel B: ETH price deviation

Notes: The figure plots the Bitcoin and Ethereum price deviations around December 13, 2015, when the Argentina government removed capital controls to increase exports and spur economic growth. Panel A plots the Bitcoin price deviations from October 18, 2015, to February 7, 2016 (16 weeks around the event date). Panel B plots the Ethereum price deviations in the same time window.

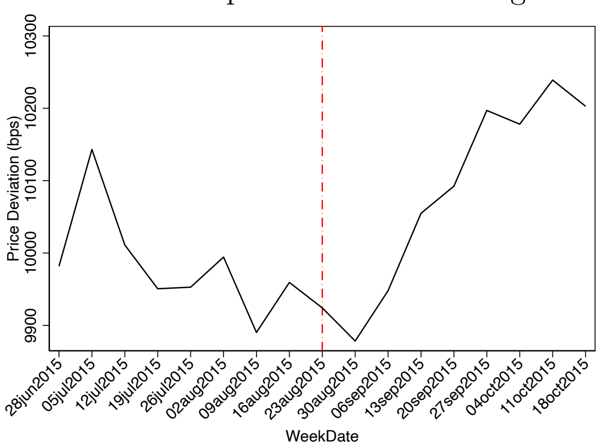
Figure A.4: Price deviation based on market exchange rate in China and Argentina



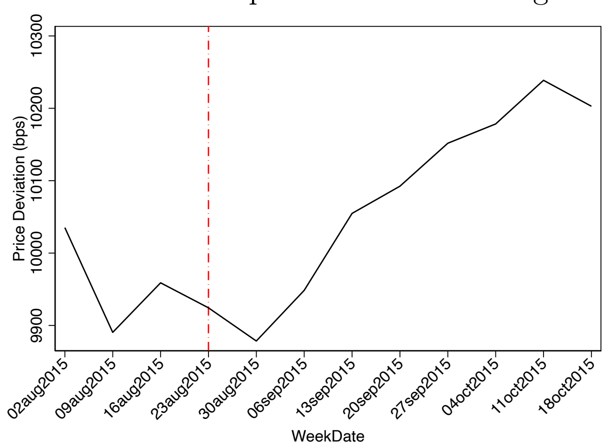
Panel A: Bitcoin price deviation in Argentina



Panel B: Ethereum price deviation in Argentina



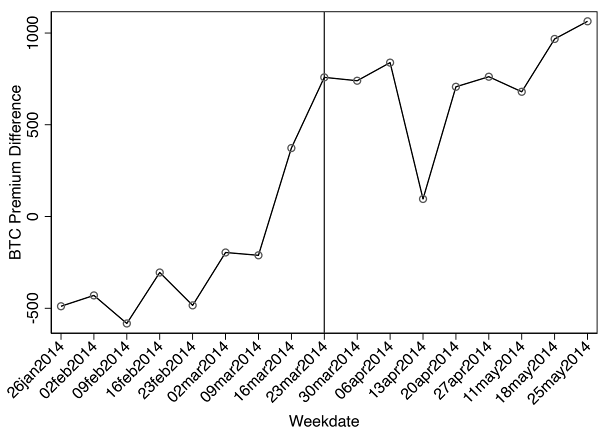
Panel C: Bitcoin price deviation in China



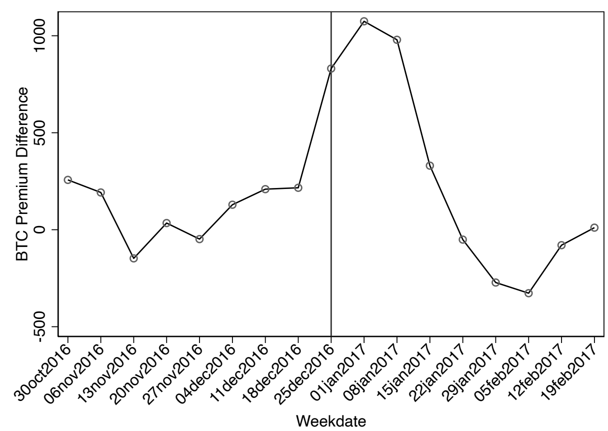
Panel D: Ethereum price deviation in China

Notes: This figure plots trend of price deviation of Bitcoin and Ethereum calculated by the market exchange rate. Panel A plots the Bitcoin price deviations from June 28 to October 18, 2015 (16 weeks around the date when the China stock market crash happened). Panel B plots the Ethereum price deviations from August 2 to October 18, 2015, as the Ethereum price data begin from August 2, 2015. Panel C plots the Bitcoin price deviations from June 7 to October 27, 2019 (16 weeks around the date when Argentina government imposed new capital controls). Panel B plots the Ethereum price deviations in the same time window.

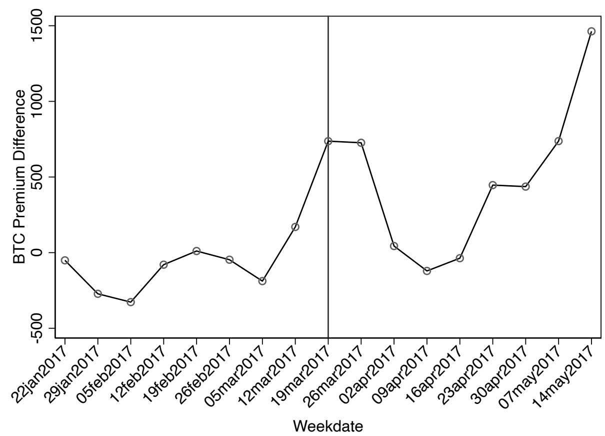
Figure A.5: Event studies: price deviations around three Brazilian political events



Panel A: Operation car wash



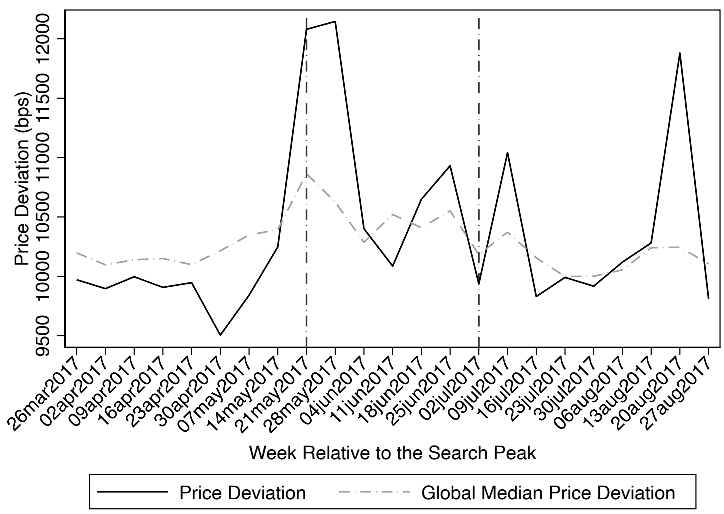
Panel B: Brazil's labor reform



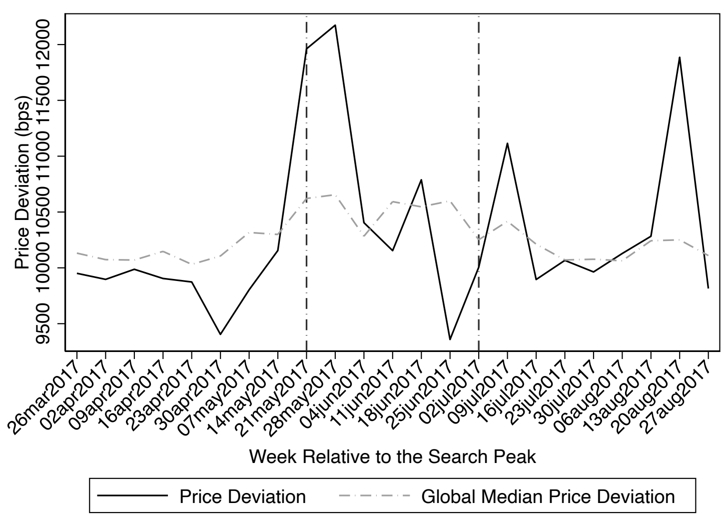
Panel C: Protests against the labor reform

Notes: The figure shows the Bitcoin price deviation around 16 weeks of the three events: Operation Car Wash known to the public on March 17, 2014, in Panel A; Brazil labor reform proposed on December 23, 2016, in Panel B; and protests against the labor reform erupted on March 15, 2017, in Panel C.

Figure A.6: Event studies: price deviations around Marawi conflict



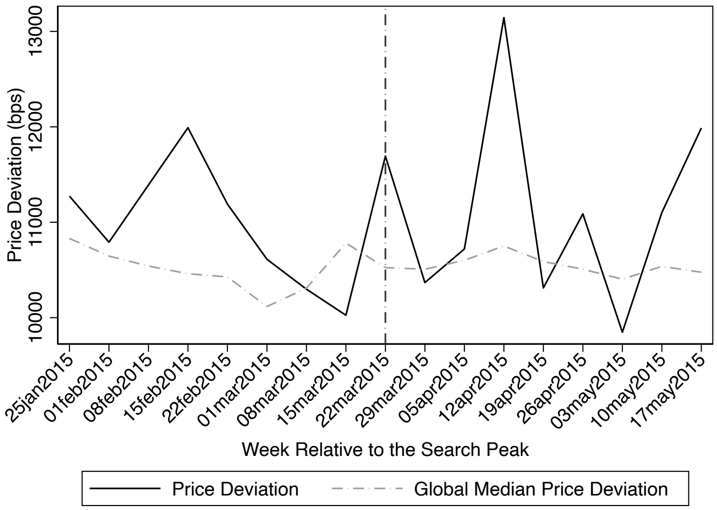
Panel A: BTC price deviation of Philippine



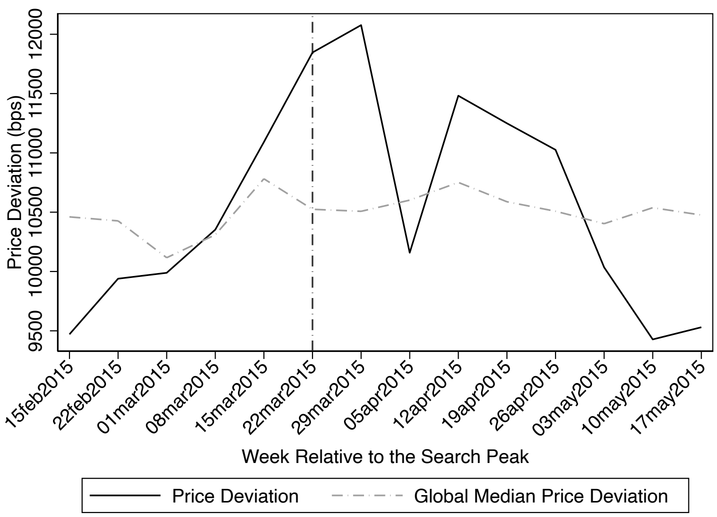
Panel B: ETH price deviation of Philippine

Notes: The figure shows the Bitcoin and Ethereum price deviation around the Marawi conflict in the Philippines. Panel A plots the trend of Bitcoin price deviation from March 26, 2017, to August 27, 2017 (16 weeks around the event date). Panel B plots the movement of Ethereum price deviation in the same time window.

Figure A.7: Event studies: price deviations around India-Pakistan conflict



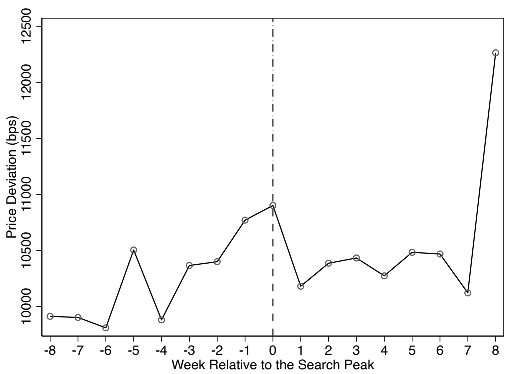
Panel A: BTC price deviation of India



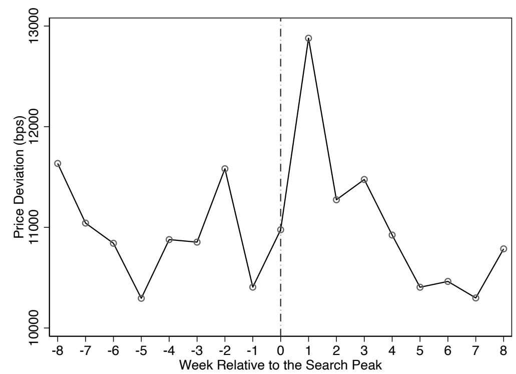
Panel B: BTC price deviation of Pakistan

Notes: The figure shows the Bitcoin and Ethereum price deviation around March 22, 2015, when the Indian-Pakistan conflict happened. Panel A plots the Bitcoin price deviations from January 25, 2015, to May 17, 2015 (16 weeks around the event date). Panel B plots the Ethereum price deviations from February 15, 2015, to May 17, 2015.

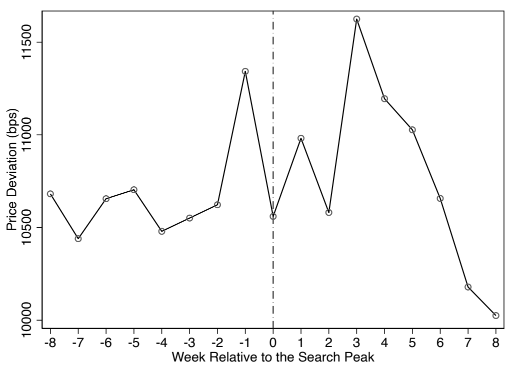
Figure A.8: Event studies: price deviations around events not inducing distrust



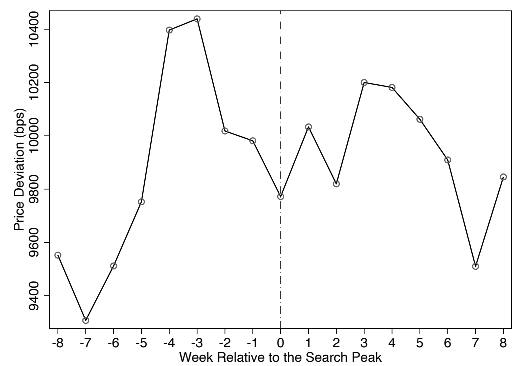
Panel A: Anti-corruption in Thailand



Panel B: Diplomatic conflict in Saudi Arabia



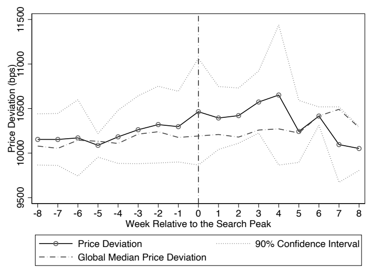
Panel C: Qatar diplomatic crisis in UAE



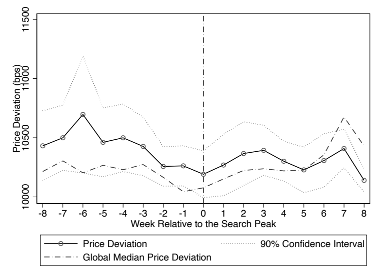
Panel D: Ceasefire deal in Colombia

Notes: This figure plots the Bitcoin price deviation around 16 weeks of 4 political scandals not inducing distrust: The anti-corruption in Thailand in Panel A, the diplomatic conflict of Saudi Arabia in Panel B, the Qatar diplomatic crisis in UAE in Panel C, and the ceasefire deal in Colombia in Panel D.

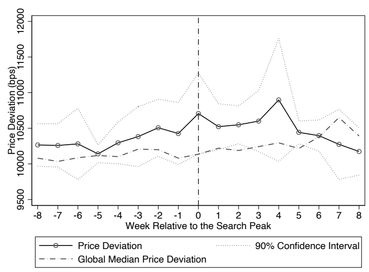
Figure A.9: Event study: price deviations around other socioeconomic events



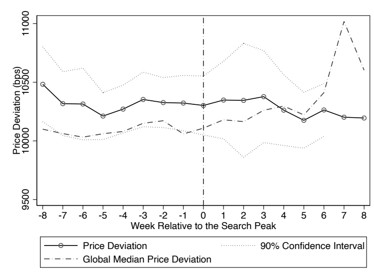
Panel A: Government-related socioeconomic Events (BTC)



Panel B: Government-unrelated socioeconomic events (BTC)



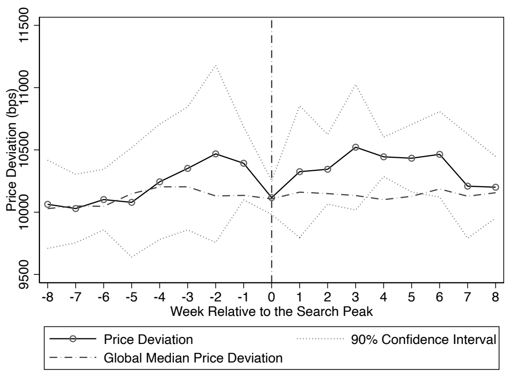
Panel C: Government-related socioeconomic Events (ETH)



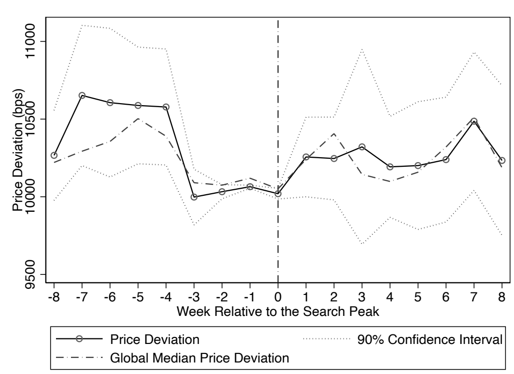
Panel D: Government-unrelated socioeconomic Events (ETH)

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 5 government-related and 6 government-unrelated socioeconomic events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panels A and C show the Bitcoin and Ethereum price deviations of government-related socioeconomic events. Panels B and D show the Bitcoin and Ethereum price deviations of government-unrelated socioeconomic events.

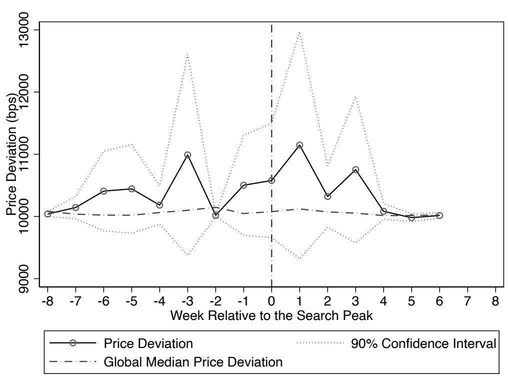
Figure A.10: Event study: price deviations around different types of irrelevant event



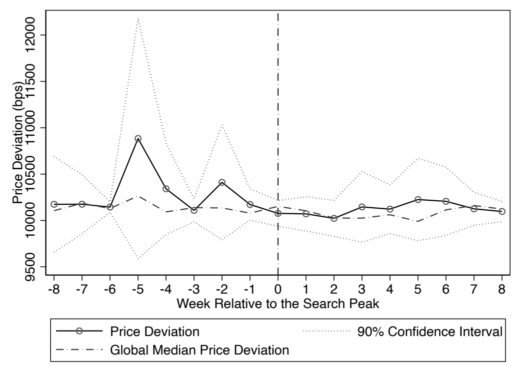
Panel A: Sex scandals



Panel B: Company scandals



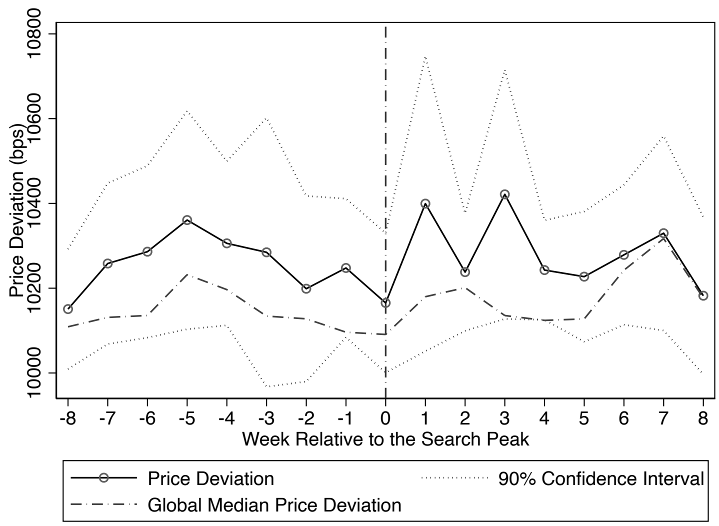
Panel C: Environmental crises



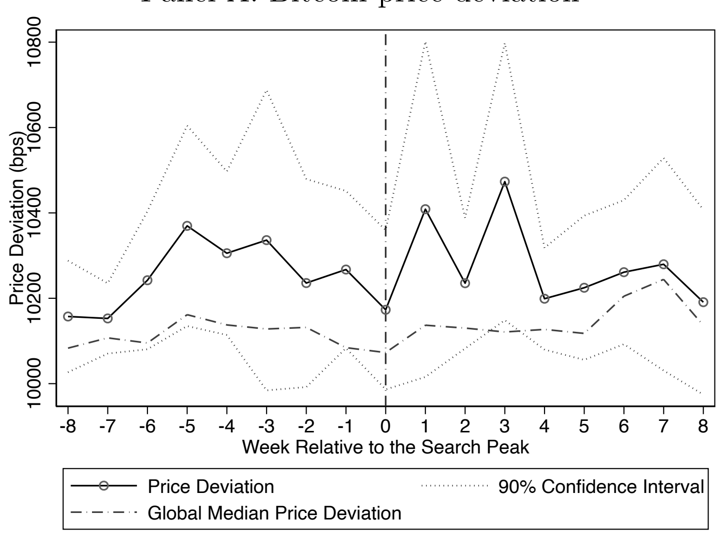
Panel D: Sports scandals

Notes: This figure plots the average Bitcoin price deviations in the 16-week time window around the event dates of four types of irrelevant events: sex scandals in Panel A, company scandals in Panel B, environmental crises in Panel C, and sports scandals in Panel D. As all three environmental crises happened in December 2019 and our data ends in January 2020, the event window is [-8,+6]. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries.

Figure A.11: Event study: price deviations around irrelevant events



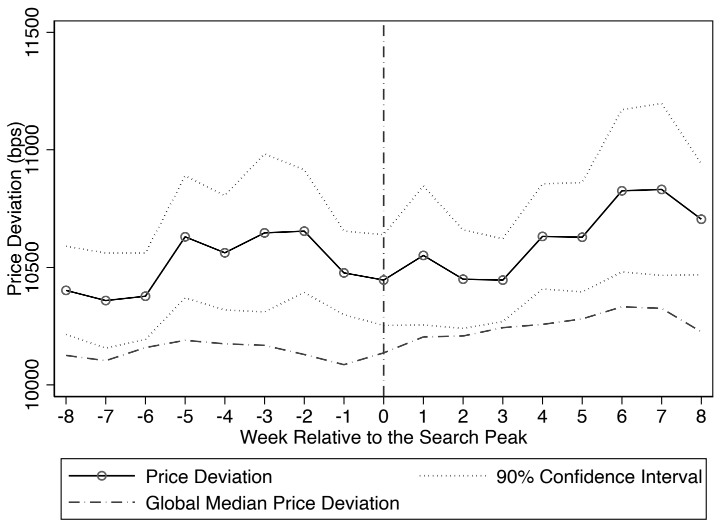
Panel A: Bitcoin price deviation



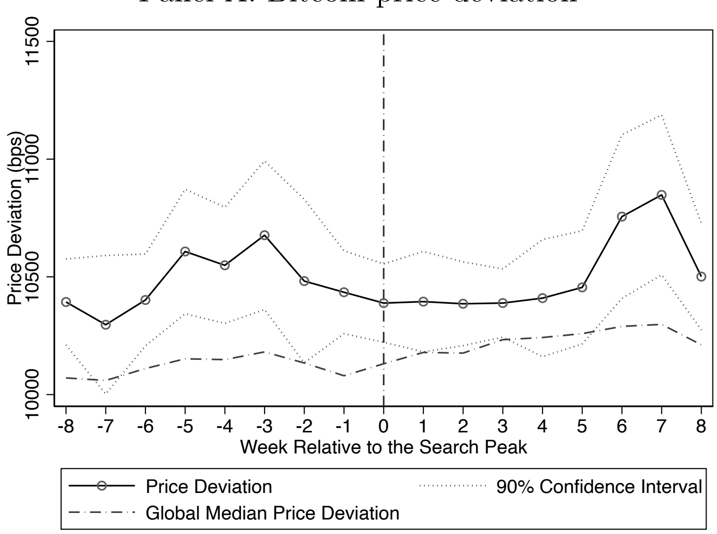
Panel B: Ethereum price deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 17 irrelevant events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panel A shows the Bitcoin price deviations, and Panel B shows the Ethereum price deviations.

Figure A.12: Event study: price deviations around unknown events



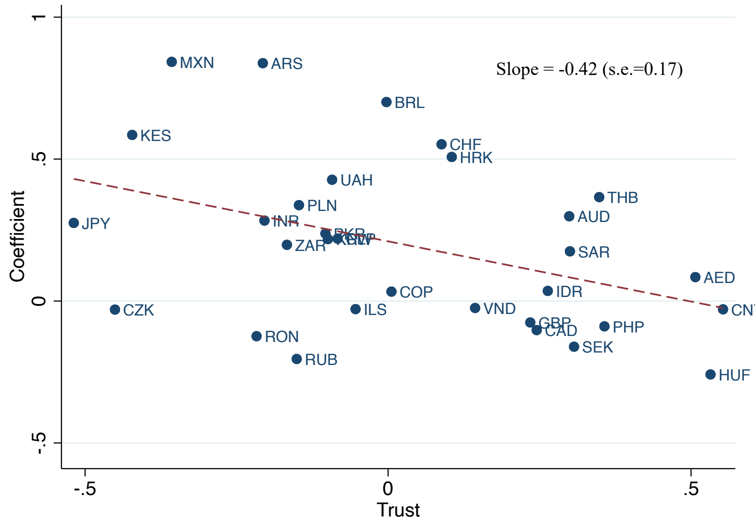
Panel A: Bitcoin price deviation



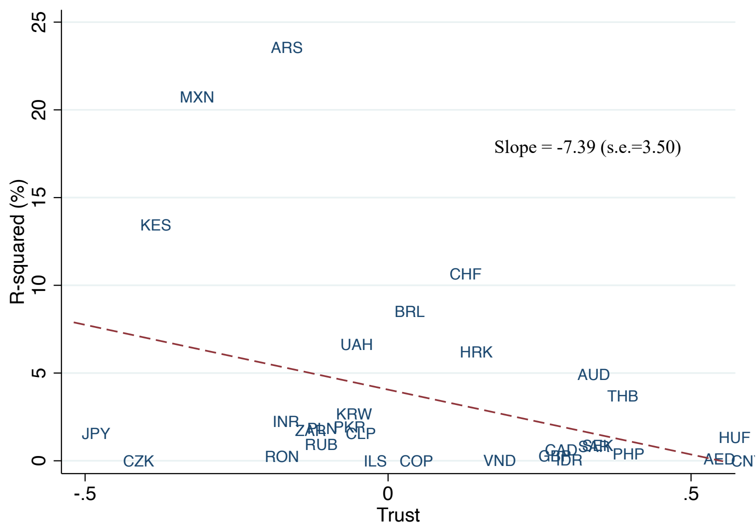
Panel B: Ethereum price deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 17 unknown events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panel A shows the Bitcoin price deviations, and Panel B shows the Ethereum price deviations.

Figure A.13: Trust, R-squared, and standardized coefficients



Panel A: Coefficients by Country and Trust



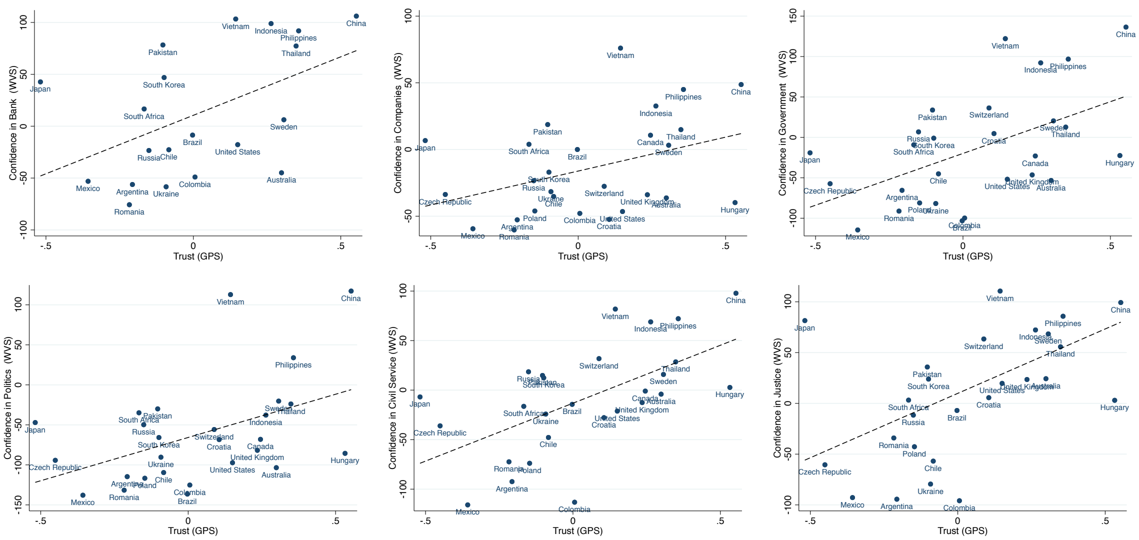
Panel B: R-squared by Country and Trust

Notes: This figure compares the explanatory power of our IFP index in the cryptocurrency price premium across the country. $\widehat{Deviation}_{c,t}$ is the normalized price deviation, which is scaled to mean zero and standard deviation of one for each country-cryptocurrency pair. We estimate the following time-series regression for each country, combining both Bitcoin and Ethereum data:

$$\widehat{Deviation}_{c,t} = \alpha_c + \beta_c IFP_{c,t} + \epsilon_{c,t}$$

Panel A correlates the trust level with β_c, and Panel B correlates the trust level with the R-squared obtained from the time-series regressions above.

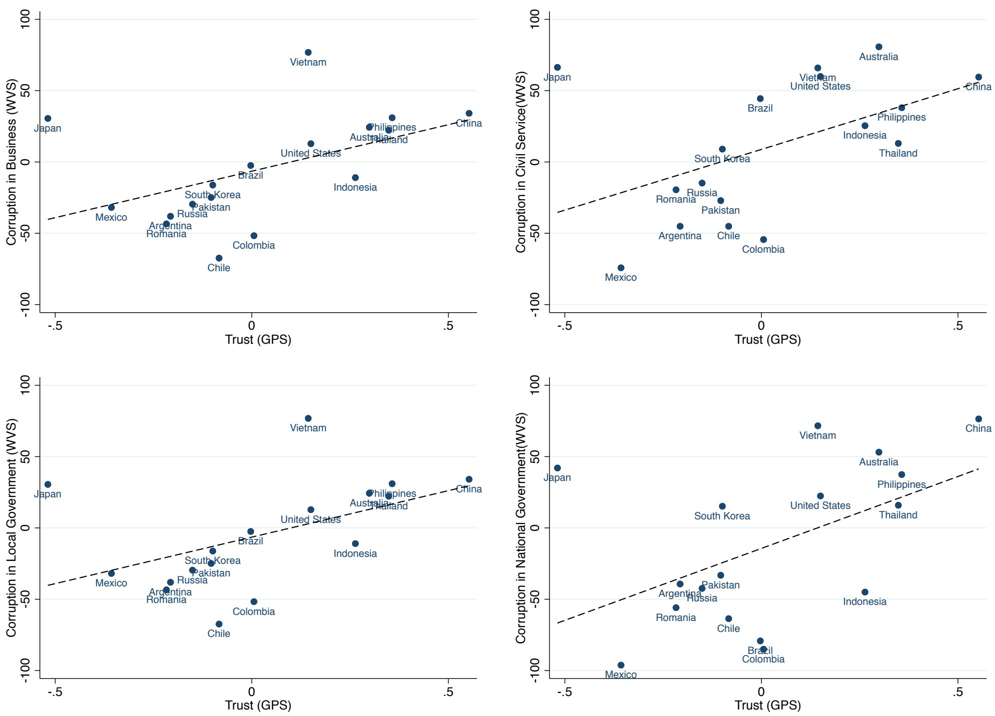
Figure A.14: Trust and confidence in institutions



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 computed from questions in the World Value Survey.

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

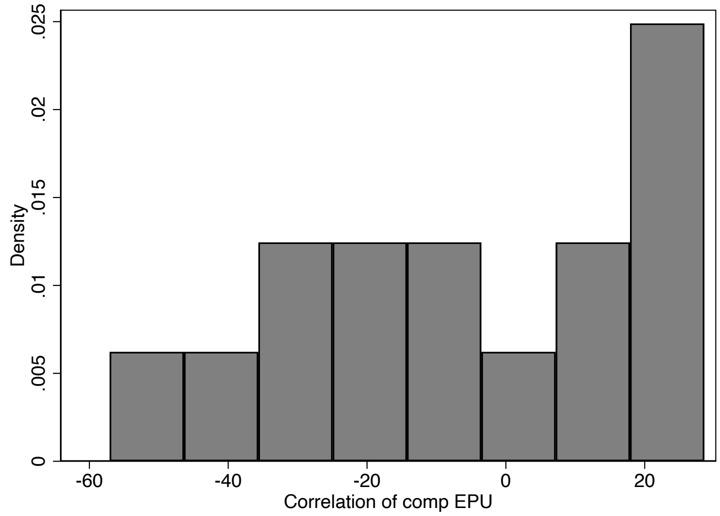
Figure A.15: Perceived corruption and trust



Notes: This figure plots the relationship between trust and perceived corruption in business, civil service, the local government, and the state/central government. The trust measure is from the Global Preference Survey, and the corruption control scores are computed from relevant questions from the World Value Survey.

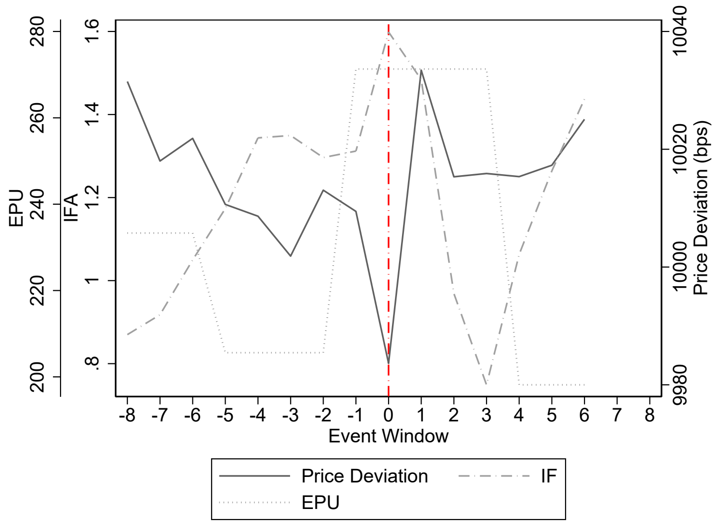
$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Figure A.16: Correlation of IFP and EPU



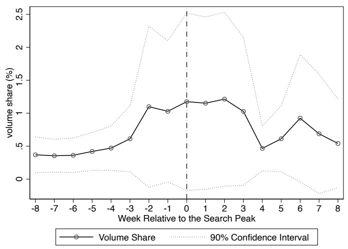
Notes: This figure plots the histogram illustrating the correlation between IFP and EPU across 15 countries.

Figure A.17: Event study: Panama tax-avoidance scandal of David Cameron

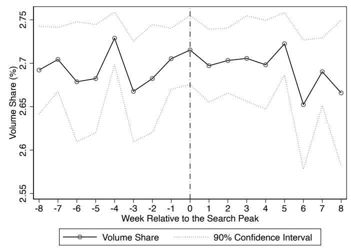


Notes: This figure plots the trend of IFP, EPU, and price deviation of Bitcoin around the Panama tax-avoidance scandal of David Cameron, the prime minister of the United Kingdom.

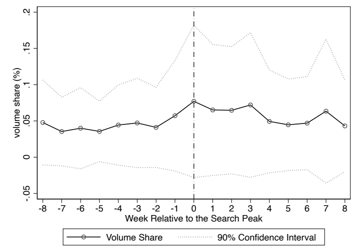
Figure A.18: Event studies: trading volume share around Google Trends peaks



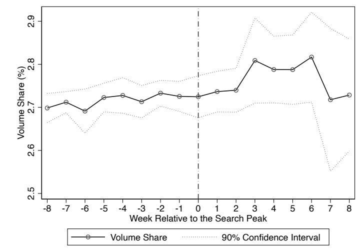
Panel A: Political scandals (BTC)



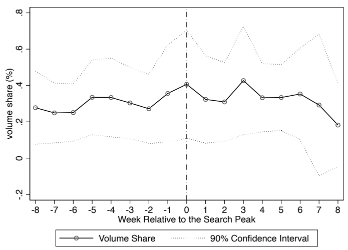
Panel B: Political scandals (ETH)



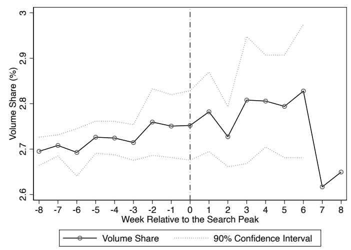
Panel C: Government-related socioeconomic events (BTC)



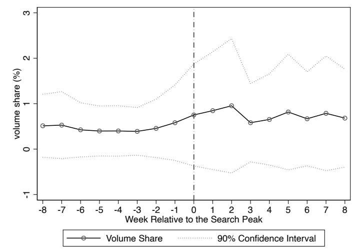
Panel D: Government-related socioeconomic events (ETH)



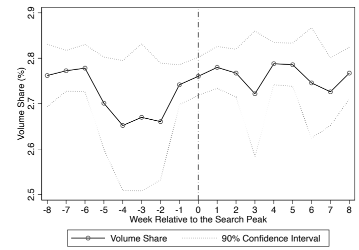
Panel E: Government-unrelated socioeconomic events (BTC)



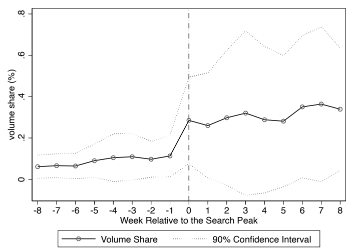
Panel F: Government-unrelated socioeconomic events (ETH)



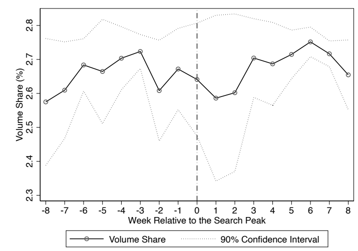
Panel G: Irrelevant events (BTC)



Panel H: Irrelevant events (ETH)



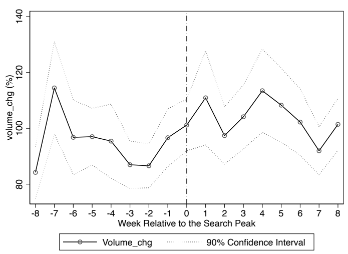
Panel I: Unknown events (BTC)



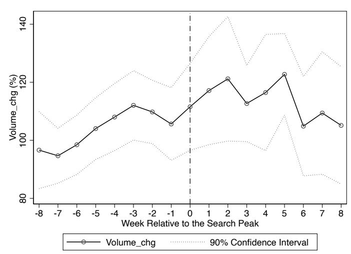
Panel J: Unknown events (ETH)

Notes: This figure reports the Bitcoin and Ethereum trading volume share in the 16-week time window around the event dates of political scandals, other socioeconomic events, irrelevant events, and unknown events. The trading volume share is the trading volume of country c divided by the total trading volume of 31 countries in week t. The dotted lines represent the 90% confidence interval.

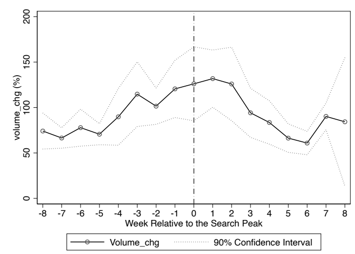
Figure A.19: Event studies: trading volume growth around Google Trends peaks



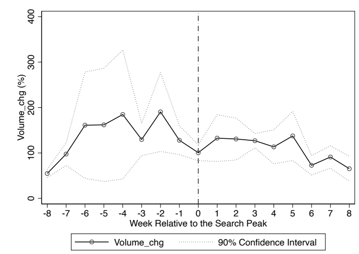
Panel A: Political scandals (BTC)



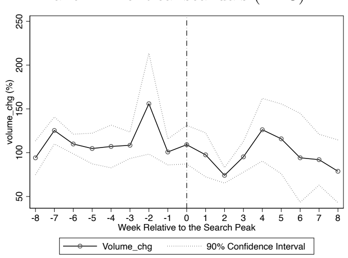
Panel B: Political scandals (ETH)



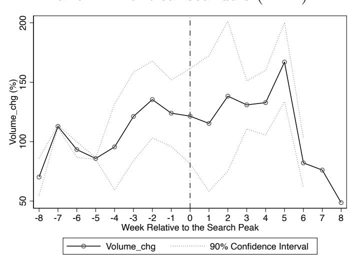
Panel C: Government-related socioeconomic events (BTC)



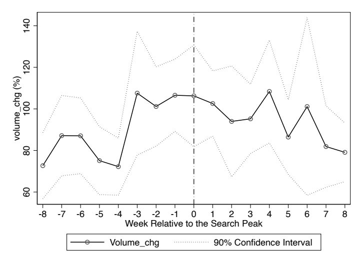
Panel D: Government-related socioeconomic events (ETH)



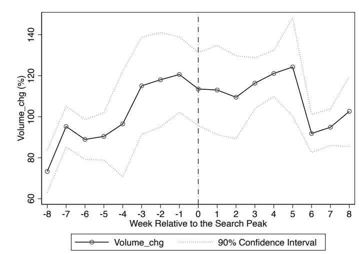
Panel E: Government-unrelated socioeconomic events (BTC)



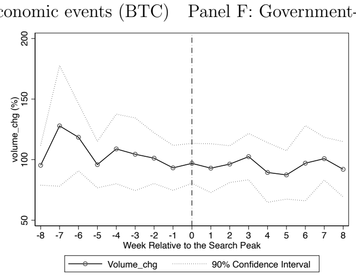
Panel F: Government-unrelated socioeconomic events (ETH)



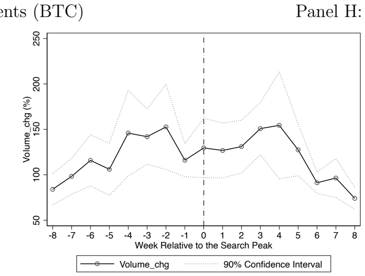
Panel G: Irrelevant events (BTC)



Panel H: Irrelevant events (ETH)



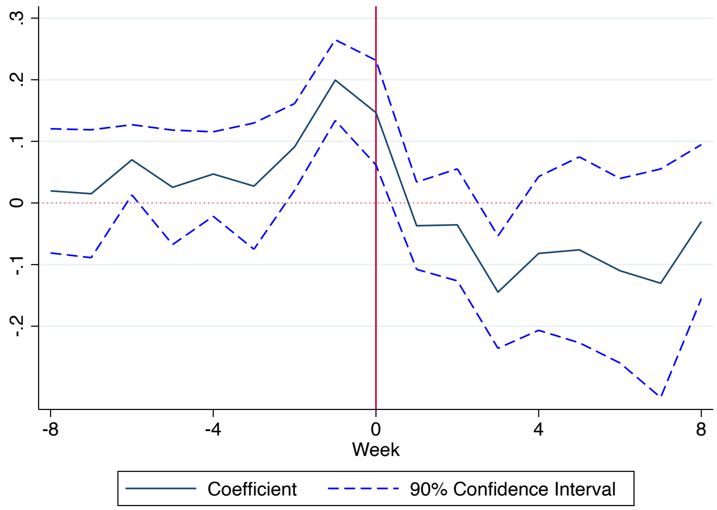
Panel I: Unknown events (BTC)



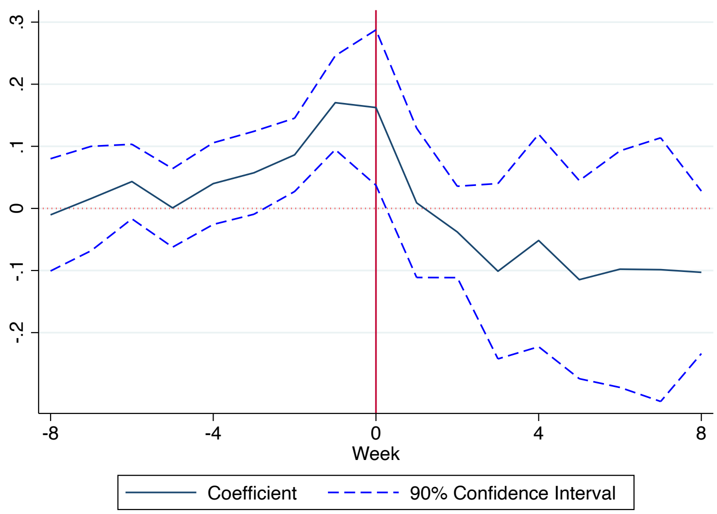
Panel J: Unknown events (ETH)

Notes: This figure reports the Bitcoin and Ethereum's trading volume growth$\Delta Volume_t = \frac{8 \times Volume_t}{\sum_{i=1}^{i=8} Volume_{t-i}}$ in the 16-week time window around the event dates of political scandals, other socioeconomic events, irrelevant events, and unknown events. The dotted lines represent the 90% confidence interval.

Figure A.20: Exchange rate and price deviation



Panel A: Bitcoin price deviation

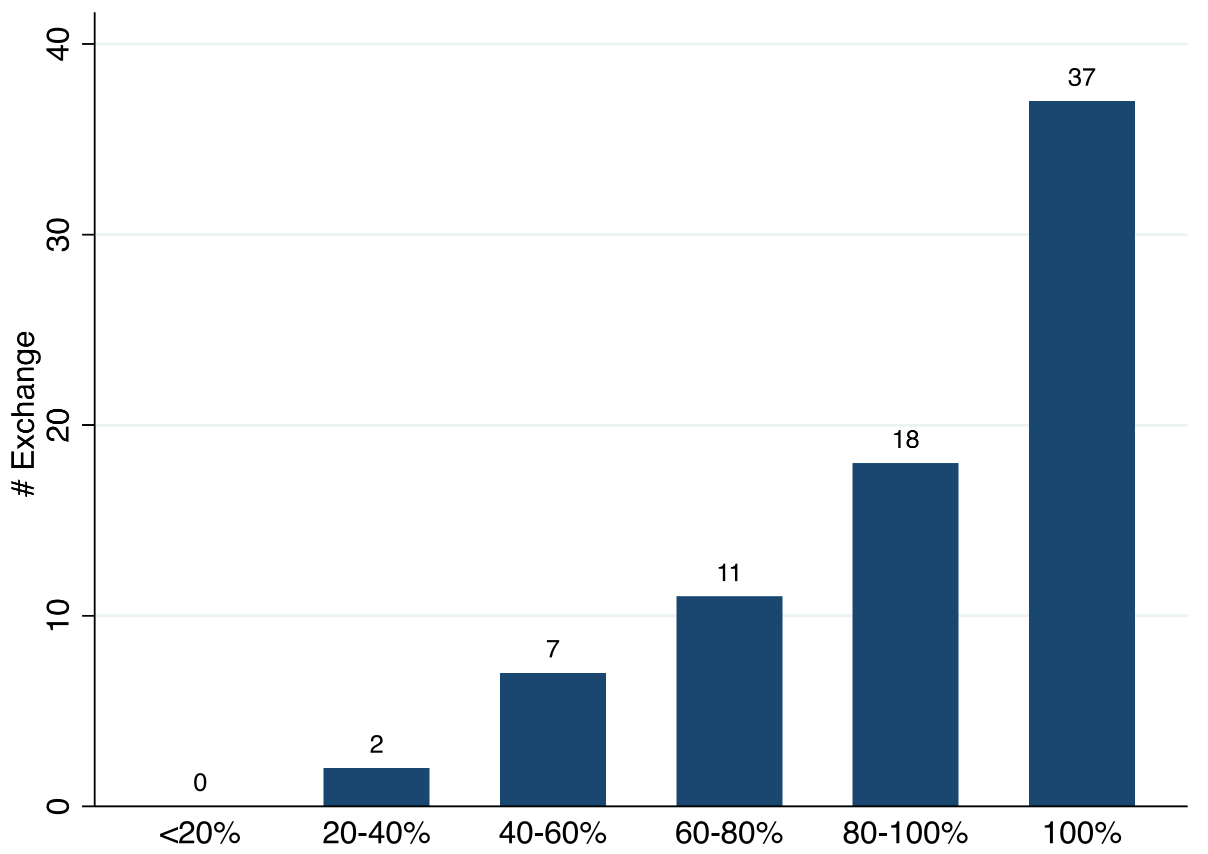


Panel B: Ethereum price deviation

Notes: This figure plots coefficients $\beta_{c,t}$ in uni-variate regressions of price deviations on lead-lag exchange rate returns from week -8 to week +8 ($i \in [-8, 8]$ in the following regression):

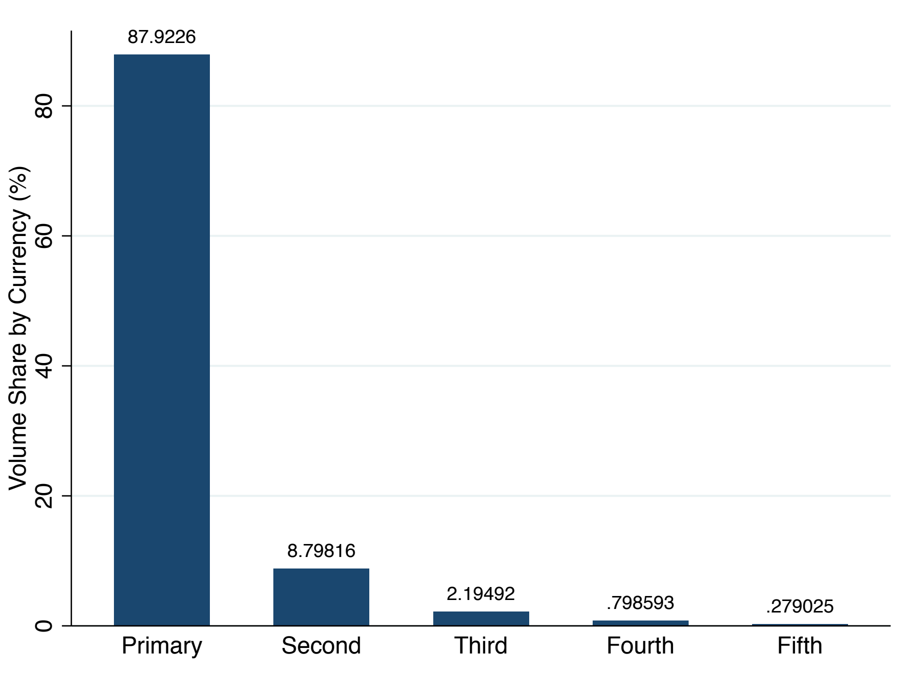
$$Deviation_{c,t} = \beta_{c,t+i} Ret^{Currency}_{c,t+i} + \gamma_c + \epsilon_{c,t}$$

Figure A.21: 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 platforms (trading happens outside the exchange): Localbitcoins and Bisq.

Figure A.22: 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 0.28% for the fifth active fiat currency.

Table A.1: Summary Statistics

Panel A summarizes cryptocurrency trading data: price deviation and trading volume. Panel B summarizes cryptocurrency and FX currency returns. Panel C summarizes variables related to Google Trends: the institutional failure probability index (IFP) and Google Trends indices for keywords "conflict," "crisis," "instability," "scandal," "bitcoin," and "ethereum." Panel D reports country features: trust scores, perceived corruption control, and confidence in various institutions. The price deviations for BTC and ETH are reported in basis points.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	S.D.	25^{th} Percentile	Median	75^{th} Percentile	Obs.
Panel A: Crypto Trading Data						
$Deviation\_BTC$	10312.16	1323.48	9975.70	10143.15	10511.62	7,688
$Deviation\_ETH$	10236.81	1390.78	9963.39	10130.68	10476.38	6,943
$LogVolume\_BTC$	5.61	3.06	3.44	5.06	7.77	7,688
$LogVolume\_ETH$	15.75	1.40	15.15	15.86	16.50	6,943
Panel B: Crypto and Currency Returns						
$Ret^{BTC}_{USD,t-9\to t-1}$	0.18	0.41	-0.082	0.079	0.36	7,688
$Ret^{ETH}_{USD,t-9\to t-1}$	0.53	1.50	-0.22	0.062	0.49	6,917
$Ret^{Currency}_{c,t-9\to t-1}$	1.00	0.038	0.98	1.00	1.01	7,688
Panel C: Google Search Data						
IFP	-0.1	0.97	-0.82	-0.21	0.55	7,688
$GT\_Conflict$	181.34	65.46	126.53	181.23	227.12	7,688
GT_Crisis	143.94	61.51	100.88	140.10	184.19	7,688
$GT\_Instability$	124.19	63.67	76.50	113.53	166.21	7,688
$GT\_Scandal$	165.65	55.14	128.92	162.33	201.42	7,688
$GT\_Bitcoin$	13.16	14.78	4	9	16	7,688
$GT\_Ethereum$	14.78	17.24	4	9	18	6,943
GT_Gold	61.96	15.41	52	63	73	7,688
$\Delta GT\_Bitcoin$	1.05	0.38	0.83	0.99	1.18	7,688
$\Delta GT\_Ethereum$	1.10	0.79	0.73	0.95	1.27	6,943
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

Table A.2: Event study on Brazil economic slowdown

This table reports the regression results for the relationship between cryptocurrency price deviation and the cumulative return of the Brazilian Real from April 26, 2014, to March 2, 2017. The dependent variable is the price deviation in Columns (1), (3), and (4), and is the adjusted price deviation (the raw price deviation minus its global median) in Column (2). We control the weekly return of the Brazilian Real in Column (3) and the GDP of Brazil in Column (4). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Ethereum price deviation. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$			
	(1)	(2)	(3)	(4)
Curindex	-1079.866**	-1396.267***	-1160.968***	-1172.267***
	(427.270)	(397.033)	(419.938)	(437.304)
Logretcur			3964.104**	
			(1734.322)	
GDP				-11.212
				(10.075)
# Observation	101	101	101	101
	Panel B: Dependent Variable $Deviation_{ETH}$			
Curindex	-1107.358**	-1214.745***	-1283.889**	-1442.359**
	(514.423)	(456.445)	(511.480)	(560.872)
Logretcur			4274.506**	
			(2041.754)	
GDP				-28.589
				(19.710)
# Observation	87	87	87	87

Table A.3: Robustness event study: political events

This table reports the results of the event study by whether political events induce distrust: all events in Column (1), political scandals inducing distrust in Column (2), and political events not generating distrust toward government in Column (3). The dependent variable is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$		
	(1)	(2)	(3)
Post	199.858***	203.493***	165.391
	(56.452)	(61.918)	(88.076)
# events	43	39	4
	Panel B: Dependent Variable $Deviation_{ETH}$		
Post	177.571***	174.812***	211.402
	(50.961)	(54.718)	(102.037)
# events	41	38	3

Table A.4: Event studies on the price deviation based on euro crypto price

This table reports the pre and post changes in price deviation based on EUR crypto price for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unknown events (unidentified Google Trends spikes) in Column (5). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Bitcoin price deviation minus the global median deviation. In Panel C, the dependent variable is the Ethereum price deviation. In Panel D, the dependent variable is the Ethereum price deviation minus the global median deviation. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	199.921***	217.413**	-202.281	16.297	84.691
	(55.783)	(61.507)	(134.684)	(67.375)	(98.278)
	Panel B: Dependent Variable $Adjusted\_Deviation_{BTC}$				
Post	135.531***	101.929	-147.119	-14.412	-8.765
	(41.643)	(65.722)	(92.043)	(63.130)	(103.541)
# events	43	5	6	17	17
	Panel C: Dependent Variable $Deviation_{ETH}$				
Post	152.517***	235.752*	11.571	13.107	28.475
	(48.601)	(81.235)	(25.678)	(60.218)	(79.117)
	Panel D: Dependent Variable $Adjusted\_Deviation_{ETH}$				
Post	91.021***	90.752	-135.847	-10.505	-77.501
	(32.198)	(91.187)	(158.574)	(66.833)	(68.945)
# events	41	4	4	15	17

Table A.5: Event studies on Google Trends index

This table reports the pre and post changes in attention to Bitcoin, Ethereum, and gold for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Google Trends index of "Bitcoin". In Panel B, the dependent variable is the Google Trends index of "Ethereum". In Panel C, the dependent variable is the Google Trends index of "gold". Event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable *GT_Bitcoin*				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	5.395**	6.613	7.898	1.169	6.017
	(2.035)	(6.837)	(8.201)	(2.825)	(4.012)
# events	48	5	6	17	17
	Panel B: Dependent Variable *GT_ETH*				
Post	6.407**	11.308	15.335	2.528	7.897
	(2.610)	(10.387)	(13.722)	(3.658)	(4.731)
# events	46	4	4	15	17
	Panel C: Dependent Variable *GT_Gold*				
Post	1.189*	-0.850	6.977	0.487	0.333
	(0.681)	(2.319)	(4.416)	(2.339)	(1.620)
# events	48	5	6	17	17

Table A.6: Robustness: price deviation responses to institutional failures

This table reports robustness check for panel regressions of price deviation on the institutional failure probability index (IFP) as the principal component of the cumulative Google Trends index of "conflict," "crisis," "instability," and "scandal." The raw indices range from 0 to 100. The cumulative Google Trends index is defined as the eight-week discounted sum with a range of rate from 20% to 100%, where 20% is reported in Column(1), 40% is reported in Column(2), 60% is reported in Column(3), 80% is reported in Column(4), and 100% is reported in Column(5):

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

where $GT_{c,t}$ is the cumulative Google Trends index in country c, $Google_{c,t}$ denotes the raw weekly Google Trends index and d is the discount factor. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) 20%	(2) 40%	(3) 60%	(4) 80%	(5) 100%
IFP	95.141**	111.330**	139.910**	179.002**	203.568***
	(43.835)	(49.727)	(58.173)	(68.183)	(72.773)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
IFP	57.274*	67.803*	88.747**	121.147***	145.407***
	(30.522)	(33.936)	(38.453)	(43.121)	(44.982)
# observation	6,943	6,943	6,943	6,943	6,943

Table A.7: Correlation matrix of cumulative Google Trends indices

This table reports the correlation, mean, and standard deviation of the institutional failure probability index (IFP) and cumulative Google keyword search indices of four keywords: "conflict," "crisis," "instability," and "scandal". The raw indices range from 0 to 100. The cumulative Google Trends index is defined as the eight-week discounted sum with a rate of 80%:

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

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

	IFP	Conflict	Crisis	Instability	Scandal
IFP	100%				
Conflict	87.99%	100%			
Crisis	26.10%	15.45%	100%		
Instability	78.85%	45.62%	-5.24%	100%	
Scandal	10.58%	13.55%	4.57%	-2.64%	100%
Mean	-0.094	181.34	143.93	124.19	165.65
S.D.	1.20	65.46	61.51	63.67	55.14

Table A.8: Price deviation responses with country features

This table reports regressions that horse-race IFP with other country features $Feature_{c,y}$: GDP per capita growth in Column (2), credit by the private sector in Column (3), annual inflation in Column (4), the WGI rule of law index in Column (5), WGI government effectiveness index in Column (6), WGI corruption control score in Column (7), and weekly exchange rate return of local currency in Column (8).

$$Deviation_{c,t} = \beta_1 IFP_{c,t} + \beta_2 Feature_{c,y} + \gamma_c + \epsilon_{c,t}$$

where $IFP_{c,t}$ denotes the institutional failure index. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$							
	(1) N/A	(2) GDP Growth	(3) Credit	(4) Inflation	(5) Law	(6) Gov Eff	(7) Corruption	(8) Currency Return
IFP	179.002**	195.844**	161.081**	113.700**	176.445***	182.111**	167.740***	179.379**
	(68.183)	(76.134)	(63.596)	(47.518)	(61.746)	(68.268)	(57.404)	(68.119)
Feature		6.530	-5.140	22.361***	-1168.374	-192.691	-1281.128	1501.522**
		(5.415)	(11.035)	(5.816)	(1007.516)	(498.590)	(897.063)	(646.309)
Currency FE	YES	YES	YES	YES	YES	YES	YES	YES
# observation	7,688	7,688	7,030	7,440	7,440	7,440	7,440	7,688
	Panel C: Dependent Variable $Deviation_{ETH}$							
IFP	121.147***	133.478***	125.229***	94.104**	121.927***	123.972***	120.537***	121.115***
	(43.121)	(45.696)	(44.966)	(39.721)	(41.478)	(43.533)	(41.737)	(43.077)
Feature		8.575**	13.495	29.087**	-831.800	46.686	-761.633	1467.001
		(4.063)	(15.863)	(13.813)	(746.187)	(467.397)	(581.973)	(921.021)
Currency FE	YES	YES	YES	YES	YES	YES	YES	YES
# observation	6,943	6,943	6,332	6,717	6,717	6,717	6,717	6,943

Table A.9: Price deviation responses with country features controlling week fixed effects

This table reports regressions that horse-race IFP with other country features $Feature_{c,y}$: GDP per capita growth in Column (2), credit by the private sector in Column (3), annual inflation in Column (4), the WGI rule of law index in Column (5), WGI government effectiveness index in Column (6), WGI corruption control score in Column (7), and weekly exchange rate return of local currency in Column (8).

$$Deviation_{c,t} = \beta_1 IFP_{c,t} + \beta_2 Feature_{c,y} + \gamma_c + \epsilon_{c,t}$$

where $IFP_{c,t}$ denotes the institutional failure index. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country and week fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$							
	(1) N/A	(2) GDP Growth	(3) Credit	(4) Inflation	(5) Law	(6) Gov Eff	(7) Corruption	(8) Currency Return
IFP	121.753*	123.113*	111.884	60.271	108.481*	120.721*	102.432*	122.289*
	(66.068)	(67.091)	(68.285)	(48.238)	(58.544)	(64.491)	(58.997)	(66.110)
Feature		11.119	-1.641	21.714***	-1221.885	-177.432	-1255.144	1488.274**
		(10.353)	(9.561)	(5.650)	(975.709)	(535.380)	(798.952)	(609.263)
Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES	YES	YES
# observation	7,688	7,688	7,030	7,440	7,440	7,440	7,440	7,688
	Panel D: Dependent Variable $Deviation_{ETH}$							
IFP	175.050**	174.631**	180.092**	153.866*	170.768**	178.954**	172.486**	175.321**
	(79.558)	(79.026)	(80.805)	(81.076)	(82.184)	(80.423)	(80.053)	(79.493)
Feature		4.559	17.267	28.058**	-728.744	134.451	-621.567	1031.230
		(6.496)	(15.612)	(11.167)	(830.564)	(493.913)	(590.321)	(907.993)
Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES	YES	YES
# observation	6,943	6,943	6,332	6,717	6,717	6,717	6,717	6,943

Table A.10: Price deviation responses with currency return control

This table reports the results of the effects of currency depreciation. We control the log cryptocurrency return in the past eight weeks in Column (2), the log return of local currency in Column (3), the cumulative log return of local currency in Column (4), and all three variables in Column (5). The independent variable is the Bitcoin price deviation in Panel A, and the Ethereum price deviation in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$			
	(1)	(2)	(3)	(4)
IFP	179.002**	179.379**	160.523***	160.892***
	(68.183)	(68.119)	(55.241)	(55.209)
Logretcur		1501.522**		920.632
		(646.309)		(723.453)
Curindex			981.834***	974.551***
			(108.191)	(111.420)
# Observation	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$			
IFP	121.147***	121.115***	119.217***	119.277***
	(43.121)	(43.077)	(42.174)	(42.145)
Logretcur		1467.001		1335.180
		(921.021)		(916.928)
Curindex			242.067**	230.921**
			(107.302)	(104.146)
# Observation	6,943	6,943	6,943	6,943

Table A.11: Price deviation responses with cryptocurrency return control

This table reports the response of cryptocurrency price deviation to the institutional failure controlling for the past eight-week cryptocurrency returns. The independent variable is the institutional failure probability index (IFP) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5). Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IFP	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	172.874**	142.680**	59.109*	127.459**	88.098**
	(68.380)	(64.198)	(31.937)	(60.315)	(39.823)
$Ret^{BTC}_{USD,t-9\to t-1}$	165.345**	162.895**	170.826**	180.184***	178.882***
	(65.218)	(64.700)	(64.656)	(65.229)	(63.576)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	111.665**	83.314*	29.142	110.255	-27.351
	(46.232)	(45.195)	(27.323)	(70.532)	(60.579)
$Ret^{ETH}_{USD,t-9\to t-1}$	10.286	11.417	16.688	16.345	21.066
	(18.877)	(18.312)	(17.774)	(18.316)	(15.165)
# observation	6,917	6,917	6,917	6,917	6,917

Table A.12: Price deviation based on euro cryptocurrency price responses

This table reports panel regressions of the cryptocurrency price deviation calculated from euro crypto price on the institutional failure probability index (IFP) in Column (1) and cumulative Google Trends for "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5) by estimating the following regressions:

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

where $GT_{c,t}$ denotes the IFP and cumulative Google Trends indices. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IFP	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	176.562**	144.339**	63.365*	131.387**	84.237**
	(67.356)	(63.474)	(32.868)	(60.360)	(40.106)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	125.101***	91.070**	33.288	129.982*	-20.118
	(42.813)	(42.703)	(27.715)	(68.558)	(61.023)
# observation	6,943	6,943	6,943	6,943	6,943

Table A.13: Cryptocurrency attention responses with crypto return control

This table reports the response of "Bitcoin" and "Ethereum" Google search growth to the institutional failure probability index (IFP) and four institutional failures ("conflict," "crisis," "instability," and "scandal") controlling for past eight-week cryptocurrencies returns. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $\Delta GT\_Bitcoin$				
	(1) IFP	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	0.061***	0.047***	0.043***	0.040**	0.018
	(0.015)	(0.014)	(0.015)	(0.015)	(0.012)
$Ret^{BTC}_{USD,t-9\rightarrow t-1}$	0.423***	0.422***	0.422***	0.428***	0.427***
	(0.068)	(0.069)	(0.068)	(0.069)	(0.070)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $\Delta GT\_Ethereum$				
Google Trends	0.106***	0.100***	0.072**	0.040	0.032
	(0.036)	(0.033)	(0.028)	(0.032)	(0.023)
$Ret^{ETH}_{USD,t-9\rightarrow t-1}$	0.137***	0.136***	0.141***	0.144***	0.142***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
# observation	6,917	6,917	6,917	6,917	6,917

Table A.14: Attention to "gold" and institutional failures

This table reports regressions of Google Trends index of "gold" on the institutional failure probability index (IFP) in Column (1) and the cumulative Google search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5).

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

where $GT_{c,t}$ denotes the institutional failure probability index (IFP) and the cumulative Google Trends index of keywords related to institutional failures. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable ΔGT_Gold				
	(1) IFP	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	-0.00228	-0.00258	0.000525	-0.000543	-0.00635*
	(0.00346)	(0.00348)	(0.00330)	(0.00353)	(0.00325)
# obsercation	7,688	7,688	7,688	7,688	7,688

Table A.15: Heterogeneous price deviation response to Google Trends by trust

This table reports the Bitcoin price deviation responses to Google Trends indices for "conflict," "crisis," "instability," and "scandal," and the heterogeneous effects by country's trust level. High-trust countries in Column (2) refer to 11 countries with Global Preference Survey (GPS) trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a trust score between -0.1 and 0.2. In Column (4), low-trust countries 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 Google Trends indices for "conflict," "crisis," "instability," and "scandal." $Distrust_c$ is omitted as currency fixed effects fully absorb it. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
GT_Conflict	149.784**	-32.772	253.918**	279.347*	-362.174**
	(62.977)	(41.424)	(105.588)	(152.426)	(150.654)
GT_Conflict × *Distrust*					8.289***
					(2.856)
GT_Crisis	67.093**	5.403	115.243	134.330**	-135.374*
	(30.762)	(19.100)	(84.639)	(51.388)	(74.394)
GT_Crisis × *Distrust*					3.651**
					(1.496)
GT_Instability	125.198**	161.518	49.581	162.991*	250.927
	(60.100)	(126.066)	(102.548)	(83.010)	(292.271)
GT_Instability × *Distrust*					-1.908
					(3.995)
GT_Scandal	87.498**	-29.502	177.793**	127.287*	-147.633
	(38.156)	(61.181)	(67.172)	(61.205)	(148.711)
GT_Scandal × *Distrust*					4.366
					(2.636)
# observations	7,688	2,728	2,232	2,728	7,688

Table A.16: Heterogeneous price deviation (from euro crypto prices) responses to Google Trends

This table reports the Bitcoin price deviation (based on euro crypto price) responses to Google Trends indices for "conflict," "crisis," "instability," and "scandal," and the heterogeneous effects by country's trust level. High-trust countries in Column (2) refer to 11 countries with Global Preference Survey (GPS) trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a trust score between -0.1 and 0.2. In Column (4), low-trust countries 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 Google searches in "conflict," "crisis," "instability," and "scandal." $Distrust_c$ is omitted as currency fixed effects fully absorb it. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
GT_Conflict	149.784**	-32.772	253.918**	279.347*	-362.174**
	(64.665)	(41.883)	(109.232)	(152.389)	(149.388)
GT_Conflict × *Distrust*					8.289***
					(2.845)
GT_Crisis	67.093**	5.403	115.243	134.330**	-135.374*
	(32.260)	(19.401)	(88.834)	(51.260)	(75.052)
GT_Crisis × *Distrust*					3.651**
					(1.529)
GT_Instability	125.198**	161.518	49.581	162.991*	250.927
	(60.412)	(125.061)	(101.560)	(84.788)	(290.507)
GT_Instability × *Distrust*					-1.908
					(3.982)
GT_Scandal	87.498**	-29.502	177.793**	127.287*	-147.633
	(39.698)	(60.860)	(69.264)	(61.307)	(147.589)
GT_Scandal × *Distrust*					4.366
					(2.615)
# observations	7,688	2,728	2,232	2,728	7,688
Currency FEs	Yes	Yes	Yes	Yes	Yes

Table A.17: Heterogeneous price deviation (from euro crypto prices) responses to institutional failures

This table reports the heterogeneous price deviation based on euro crypto price response to the institutional failure probability (IFP) index by the country's trust level from Global Preference Survey (GPS). High-trust countries in Column (2) refer to 11 countries with GPS trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a GPS trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a GPS trust score below -0.1. Column (5) reports the test for heterogeneous response by trust level:

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

where $IFP_{c,t}$ denotes the IFP index. $Distrust_c$ is GPS trust score. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
IFP	176.562**	32.481	237.020	300.584*	-218.328
	(67.356)	(37.511)	(129.739)	(158.950)	(165.465)
$IFP \times Distrust$					416.025**
					(201.880)
# observation	7,688	2,728	2,232	2,728	7,688
	PanelB: Dependent Variable $Deviation_{ETH}$				
IFP	125.101***	10.473	205.395**	199.143**	-82.600
	(42.813)	(37.129)	(77.660)	(72.696)	(129.090)
$IFP \times Distrust$					220.946*
					(128.877)
# observation	6,943	2,465	1,999	2,479	6,943

Table A.18: Trust validation with questions in the World Value Survey

This table validates the trust measure in the Global Preference Survey with various questions in the World Value Survey. Panel A reports the relationship between trust and confidence in institutions, including banks, companies, government, politics, civil service, and justice. The confidence scores are calculated from the World Value Survey (WVS).

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

Panel B reports the relationship between trust and 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 (WVS).

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

Panel C 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, in people you know personally, in your neighbors, and in people you first met. Standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Trust and Confidence in Institutions					
	(1) Bank	(2) Companies	(3) Government	(4) Political	(5) Civil	(6) Justice
Trust	112.728**	50.835**	128.080***	108.101**	116.960***	119.257***
	(47.010)	(24.176)	(41.990)	(41.722)	(31.674)	(38.347)
# Currencies	20	27	27	27	27	26
	Panel B: Trust and Corruption in Institutions					
	Business	Civil	State	Local		
Trust	65.169**	85.103**	100.868**	69.728*		
	(30.369)	(38.997)	(44.849)	(36.374)		
# Currencies	17	17	17	17		
	Panel A: Trust Validation					
	Most Trusted	Know Personally	Neighbors	First Met		
Trust	20.923*	67.133*	60.377**	46.240		
	(10.419)	(34.239)	(26.097)	(30.653)		
# Currencies	28	23	23	23		

Table A.19: Robustness: price deviation responses to adjusted IFP

This table reports panel regressions of the cryptocurrency price deviation on the institutional failure probability index (IFP) in Column (1) and the $IFP_{c,t} - IFP_{global,t}$ in Columns (2) and (3). The country fixed effects are included in Panel A, whereas both country and week fixed effects are included in Panels B and D. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$		
	(1)	(2)	(3)
IFP	179.002**		
	(68.183)		
Adj_IFP		58.861**	121.753*
		(24.458)	(66.075)
Week FE	NO	NO	YES
Currency FE	YES	YES	YES
# observation	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$		
IFP	121.147***		
	(43.121)		
Adj_IFP		61.541***	175.050**
		(20.667)	(79.546)
Week FE	NO	NO	YES
Currency FE	YES	YES	YES
# events	6,943	6,943	6,943

Table A.20: Price deviation responses with EPU index

This table reports the response of cryptocurrency price deviation to the institutional failure probability index (IFP) controlling for economic policy uncertainty index (EPU). Column (1) reports the results of cryptocurrency price deviation response to IFP. Column (2) reports the results of cryptocurrency price deviation response to the EPU index. Column (3) reports the results of cryptocurrency price deviation responses to IFP controlling the EPU index. Country-fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$		
	(1)	(2)	(3)
IF	138.086**		141.537***
	(47.181)		(46.801)
EPU		0.083	0.192
		(0.307)	(0.275)
# observation	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$		
IF	63.541		68.252
	(41.510)		(41.533)
EPU		0.312	0.349
		(0.228)	(0.220)
# events	6,943	6,943	6,943

Table A.21: Event studies of trading volume by event type

This table reports the pre and post-changes in trading volume for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Bitcoin trading volume share as a percentage of the total market trading volume. In Panel B, the dependent variable is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Vol\_Bitcoin_t}{\sum_{i=1}^{i=8} Vol\_Bitcoin_{t-i}}$. In Panel C, the dependent variable is the Ethereum trading volume share as a percentage of the total market trading volume. In Panel D, the dependent variable is the Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Vol\_Ethereum_t}{\sum_{i=1}^{i=8} Vol\_Ethereum_{t-i}}$. As there are outliers in the Ethereum trading volume for the Indian stock market crash, we dropped this event in our analysis. Event-fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable Vol_Share_{BTC}				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	0.319	0.012	0.006	0.287	0.223
	(0.314)	(0.012)	(0.022)	(0.315)	(0.186)
# events	48	5	6	17	17
	Panel B: Dependent Variable $\Delta Vol\_Bitcoin$				
Post	8.937*	4.556	-16.886**	4.503	-10.319
	(5.062)	(7.407)	(6.226)	(11.817)	(13.544)
# events	44	4	6	15	11
	Panel C: Dependent Variable Vol_Share_{ETH}				
Post	0.006	0.054	0.072	0.052	0.0002
	(0.009)	(0.032)	(0.037)	(0.036)	(0.0002)
# events	46	4	4	15	15
	Panel D: Dependent Variable $\Delta Vol\_Ethereum$				
Post	9.457	12.609	15.305*	10.327	0.529
	(6.028)	(7.352)	(6.281)	(6.884)	(14.836)
# events	43	3	4	10	14

Table A.22: Trading volume response to institutional failures

This table reports panel regressions of trading volume on the institutional failure probability index (IFP) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), "scandal" in Column (5). In Panel A, the dependent variable is the Bitcoin trading volume share as a percentage of the total market trading volume. In Panel B, the dependent variable is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Vol\_Bitcoin_t}{\sum_{i=1}^{i=8} Vol\_Bitcoin_{t-i}}$. In Panel C, the dependent variable is the Ethereum trading volume share as a percentage of the total market trading volume. In Panel D, the dependent variable is the Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Vol\_Ethereum_t}{\sum_{i=1}^{i=8} Vol\_Ethereum_{t-i}}$. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) IF	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
	Panel A: Dependent Variable Vol_Share_{BTC}				
Google Trends	0.707	0.480	0.365	0.720	-0.404
	(1.353)	(1.156)	(0.494)	(0.932)	(0.714)
# observation	7,615	7,615	7,615	7,615	7,615
	Panel B: Dependent Variable $\Delta Vol\_Bitcoin$				
Google Trends	23.534	12.056	3.858	31.907	13.610
	(32.465)	(18.293)	(16.238)	(38.858)	(12.891)
# observation	7,494	7,494	7,494	7,494	7,494
	Panel C: Dependent Variable Vol_Share_{ETH}				
Google Trends	0.043	0.048*	0.001	0.024	-0.019
	(0.030)	(0.024)	(0.012)	(0.031)	(0.027)
# observation	6,908	6,908	6,908	6,908	6,908
	Panel B: Dependent Variable $\Delta Vol\_Ethereum$				
Google Trends	7.951*	8.284*	3.009	3.044	3.088
	(4.379)	(4.615)	(2.830)	(3.096)	(3.627)
# observation	6,869	6,869	6,869	6,869	6,869

Table A.23: Price deviation response to institutional failures with trading volume control

This table reports panel regressions of price deviation on the institutional failure probability index (IFP) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), "scandal" in Column (5). The trading volume control is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Volume\_Bitcoin_t}{\sum_{i=1}^{i=8} Volume\_Bitcoin_{t-i}}$ in Panel A and Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Volume\_Ethereum_t}{\sum_{i=1}^{i=8} Volume\_Ethereum_{t-i}}$ in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IF	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	171.676**	147.441**	65.735**	112.732*	73.935*
	(70.034)	(67.589)	(30.101)	(60.970)	(43.387)
$\Delta Volume\_Bitcoin$	-1.292	-1.213	-1.135	-1.240	-1.199
	(1.093)	(1.132)	(1.141)	(1.124)	(1.162)
# observation	7,494	7,494	7,494	7,494	7,494
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	114.140**	89.593*	32.577	107.543	-45.705
	(52.673)	(50.506)	(25.847)	(74.738)	(62.496)
$\Delta Volume\_Ethereum$	34.743*	34.914*	40.264**	39.358**	42.978**
	(18.179)	(18.355)	(19.054)	(18.972)	(20.416)
# observation	6,869	6,869	6,869	6,869	6,869

Table A.24: Price deviation responses to institutional failures by trading volume

This table reports the price responses to the institutional failure probabilty (IFP) index by different trading volume filters. Column (1) uses the full sample with non-missing price data. Column (2) further limits the regression to the sample with non-missing volume data. We further restrict our sample by quartile cutoff of trading volume: the sample with trading volume higher than the 25 percentile cutoff in Column (3), the sample with trading volume above the median trading volume in Column (4), and the sample with trading volume higher than the 75 percentile cutoff in Column (5). Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1)	(2)	(3)	(4)	(5)
	All	0	25th	50th	75th
IFP	179.002**	165.876**	193.569**	111.924**	100.540**
	(68.183)	(67.266)	(73.132)	(42.313)	(44.277)
# Observation	7,688	7,615	5,711	3,805	1,893
	Panel B: Dependent Variable $Deviation_{ETH}$				
IFP	121.147***	115.720**	147.339***	140.437***	94.488**
	(43.121)	(49.484)	(42.049)	(34.732)	(41.428)
# Observation	6,943	6,908	5,258	3,499	1,775

Table A.25: Price deviation predictability in FX exchange rates

This table explores whether cryptocurrency price deviations predict anything in the currency 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 change in Column (2), the future eight-week exchange rate change in Column (3), the future 24-week exchange change in Column (4), and the dummy for significant currency depreciation in next 24 weeks (defined as 24-week currency return < -15%) in Column (5). The construction of CIP deviation follows Du et al. (2018). We construct CIP deviations for 17 out of 31 countries with Bloomberg data. Robust standard errors are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: $FX_{c,t}$				
	(1) CIP	(2) 1-week FX Ret	(3) 8-week FX Ret	(4) 24-week FX	(5) Dummy (24-week Ret < -15%)
$Deviation_{c,t}$	3.88×10^{-8}	-0.00396	-0.00659	-0.0292	6.97×10^{-6}
	(8.96×10^{-8})	(0.00555)	(0.00785)	(0.0292)	(7.94×10^{-6})
# obsercation	4,216	7,657	7,440	6,944	6,944

B 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. Each observation represents a Google Trends peak by each currency keyword. Column "Date" provides the year-month for each event, "Short Title" refers to the event name, "Description" provides a short narrative of these events, and "Excluded" indicates whether this search peak is included in our event studies: 0 indicates the event is included in our analysis; 1 indicates this event is excluded because of lack of data; 2 indicates that the event is excluded because of too many outliers in the cryptocurrency price data as liquidity was low in earlier years. "Induce Distrust" equals 1 if a political or socioeconomic event can reduce trust in government or disappointment in the domestic economy; otherwise 0.

Events of Google Search Peaks

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
Panel A: Major Economic and Financial Crises						
ARS	crisis	2018.08	Argentine monetary crisis	Argentine peso devalued severely in 2018 because of the high inflation and capital outflow as the currency continually lost purchasing power. As a result, Argentina's government tightened the capital control on September 1, 2019. Mauricio Macri, the president of Argentina, required the companies to seek central bank permission to purchase foreign currency and to make transfers abroad. He also limited that individuals can purchase up to $10,000 US dollar per month.	0	
BRL	crisis	2014.06	Brazilian economic crisis	Brazil's economy slowed down in 2014, and the GDP decreased while the unemployment rate and inflation increased from 2014 to 2016. After 2016, a slight economic recovery began.	0	
CNY	crisis	2015.08	Chinese stock market crash	The Chinese stock market crash began on June 15, 2015. Shanghai Composite Index (SSE) continued to drop despite numerous efforts by the regulator to stop the stock market collapse. On August 24, the SSE composite index fell again by 8.48 percent, marking the largest single-day loss since 2007.	0	
Panel B: Political Scandals						
BRL	scandal	2015.12	Impeachment of Dilma Rousseff	Dilma Rousseff, the president of Brazil, was charged with criminal, administrative misconduct, and misappropriation of the federal budget on December 2, 2015. The petition also accused Rousseff of failing to act on the scandal at the Brazilian national petroleum company, Petrobras, and for failing to distance herself from the suspects in that investigation.	0	1
BRL	scandal	2018.02	Anti-Corruption Crusade Rot	On February 2, 2018, Luiz Inacio Lula da Silva, former president of Brazil, was re-elected as the Workers Party candidate for the 2018 presidential election in Sao Paulo. Lula was accused of corruption and money laundering in September 2016.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
CAD	scandal	2019.03	Justin Trudeau's political scandal	Jody Wilson-Raybould, the former minister of justice and attorney general, had been pressured to help a Quebec-based construction company settle a criminal case and avoid prosecution over allegations that it bribed officials in Libya for government contracts. On March 8, 2019, it was reported that the scandal could threaten the political future of the country's leader and the governance of the Liberal Party.	2	1
GBP	scandal	2015.09	David Cameron's drug scandal	In the book "Call Me Dave," former party treasurer Lord Ashcroft made allegations of drug taking and debauchery by young Mr. David Cameron, the former prime minister of the United Kindom, on September 20, 2015. The book also claimed Lord Ashcroft, the Conservative leader, did not pay UK tax on his overseas earnings.	0	1
GBP	scandal	2016.04	Panama tax-avoidance scandal	David Cameron, the former prime minister of the United Kingdom, admitted he benefited from a Panama-based offshore trust set up by his late father on April 7, 2016. He paid income tax on the dividends, but there was no capital gains tax payable, and he said he sold up before entering Downing Street.	0	1
GBP	scandal	2018.05	Jeremy Hunt property scandal	In April 2018, The Daily Telegraph revealed that Jeremy Hunt, the former chancellor of the exchequer of the United Kingdom, breached anti-money laundering legislation by failing to declare his 50% interest in a property firm to Companies House within the required 28 days.	0	1
IDR	scandal	2019.03	Widodo bribe scandal	Muhammad Romahurmuziy, the United Development Party leader, was arrested for influence-peddling at the religion ministry. This scandal may mark the end of days for Indonesia's second-oldest political party.	0	1
INR	scandal	2016.08	Journalist murdered after a scandal report	The International Federation of Journalists (IFJ) and its affiliates, the Indian Journalists Union (IJU) and the National Union of Journalists (India) (NUJI), strongly condemned the murder of journalist Kishore Dave in Gujarat, India, on August 22, 2016. The IFJ demanded swift investigation and action to bring those responsible to justice.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
JPY	scandal	2017.02	Government land sale scandal	On February 9, 2017, the central government of Japan sold the 8,770 square meter property in Toyonaka, Osaka Prefecture, to Moritomo Gakuen for around 134 million Japanese Yen, about 14% of the land's estimated value. Separately the government paid the school 131.76 million to help decontaminate the land, reducing what the government earned to only about 2 million. As the scandal unfolded, Abe, the prime minister of Japan, resigned from her position as honorary principal in late February.	0	1
KES	scandal	2018.05-06	Kenyan anti-corruption drive	In May 2018, Kenyan authorities detained more than 50 top officials and executives after widespread public anger prompted by allegations of the theft of more than $100m at government agencies.	0	1
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 Choi Tae-min, the leader of a religious cult, over President Park Geun-Hye of South Korea. Park Geun-Hye was impeached because of this scandal.	0	1
MXN	scandal	2019.03	Odebrecht corruption	Emilio Lozoya, the former president of the state-owned oil company Petróleos Mexicanos, is accused of having requested money from scandal-plagued Brazilian construction conglomerate Odebrecht to partially finance the presidential campaign of former President Enrique Peña Nieto in exchange for contracts.	2	1
PHP	scandal	2015.07	Iglesia ni Cristo leadership controversy	In July 2015, it was reported that the Iglesia ni Cristo, an independent Nontrinitarian Christian church, had expelled some of its ministers, along with high-profile members Felix Nathaniel "Angel" Manalo and Cristina "Tenny" Villanueva Manalo, for allegedly "sowing disunity" in the Church.	0	1
RON	scandal	2017.05	Prime minister resignation	In June 2017, Sorin Grindeanu was removed from the office of prime minister by the Social Democratic Party after an internal power struggle. Afterward, Mihai Tudose, a vice-president of the Social Democratic Party, became the new Prime Minister of Romania on June 26, 2017.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RUB	scandal	2017.02-03	Donald Trump's Russia Scandal	On February 26, 2017, the White House attempted to control public perceptions of a widening scandal over alleged contacts between aides to Donald Trump and Russian intelligence officials during the 2016 election, alleging that the FBI had dismissed reports of such links. However, with a Republican congressman calling for an independent inquiry, multiple congressional committees pursued investigations.	0	1
THB	scandal	2017.03	Corruption crackdown	At the behest of Prime Minister Prayut, the police, intelligence agencies, and the Interior Ministry have compiled a list of corrupt officers. Deputy Prime Minister Prawit Wongsuwan announced that these names would be "verified", and the legal actions will commence in February and March 2016.	0	0
UAH	scandal	2017.06	Sanction against Ukrainian separatists	The U.S. Treasury announced sanctions against 21 Ukrainian separatists on June 20, 2017.	0	1
VND	scandal	2016.08	Fish death scandal	Formosa Ha Tinh steel plant released toxic chemicals into the ocean and caused a massive amount of fish dead. Some suspect the government of a loose investigation on Formosa to protect the firm's $10.5 billion investment.	0	1
ZAR	scandal	2018.01	Gupta brothers' corruption	Atul and Rajesh Gupta, two brothers from the wealthy Gupta family, were accused in South Africa of profiting from their close links with former president Jacob Zuma and exerting unfair influence. The brothers fled to South Africa after a judicial commission began probing their corruption engagement.	2	1
AED	crisis	2017.06	Qatar diplomatic crisis	Saudi Arabia, the United Arab Emirates, Bahrain, and Egypt severed diplomatic relations with Qatar and banned Qatar-registered planes and ships from utilizing their airspace and sea routes. Saudi Arabia also blocked Qatar's only land crossing on June 5, 2017. The Saudi-led coalition cited Qatar's alleged support for terrorism as the main reason for their actions.	0	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
CLP	crisis	2019.10.	Chilean protests	Civil protests occurred throughout Chile in response to a rise in the Santiago Metro's subway fare, the increased cost of living, privatization, and inequality prevalent in the country in October 2019.	0	1
CZK	crisis	2019.12	Protest in Prague	Over 50,000 people rallied against Czech prime minister Babis. They urged Prime Minister Andrej Babis to step down over accusations he misused millions in EU funds.	0	1
GBP	crisis	2019.12	Election fallout	Following Boris Johnson's (British Prime Minister) election victory on December 12, 2019, people were concerned about how Johnson would achieve Brexit and how his government would attempt to heal the deep fractures within British politics.	0	1
HUF	crisis	2015.09	Hungary refugee crisis	Hungary closed down a key border crossing from Serbia overnight on September 14, 2015, leaving thousands of migrants stranded.	0	1
HUF	crisis	2019.12	Political crisis	Viktor Orbán, Hungary's prime minister, claimed to run a 'Christian' government; but one of his former allies, Iványi, denounced his government's consolidation of power and marginalization of minorities.	2	1
ILS	crisis	2019.12	Israeli political deadlock	Israelis would go to the polls to vote for the third time in 11 months. Any candidate who garnered the support of 61 members of the Knesset was required to form a coalition, but no one succeeded in doing so by December 11, 2019.	0	1
INR	crisis	2017.09	China–India border conflict	The 2017 China-India border conflict refers to the military standoff between the Indian Armed Forces and the People's Liberation Army of China over the Chinese construction of a road in Doklam near Donglang — a trijunction border area.	0	1
KES	crisis	2017.06	Kenya terrorist attacks	The five new deaths reported in Mandera brought the total number of Kenyans killed in the suspected Al Shabaab attack to 40. Government lacks preparation to fight against terrorism attacks.	1	1
KRW	crisis	2019.12	North Korea pressure	North Korea announced that the country would launch an "important experiment" of a missile-engine site before December 31, 2019, a deadline set by the political leader, Kim Jong-un.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
MXN	crisis	2019.12	Mexico–Bolivia diplomatic crisis	Juan Evo Morales Ayma, president of Bolivia from 2006 to 2019, and two cabinet members flew to Mexico on November 10, 2019, where they were offered political asylum. After that, Mexican President called Morales's resignation illegal and refused to recognize the new government of Jeanine Áñez. However, Bolivia claims that Mexico violated the UN Declaration on Territorial Asylum.	0	1
PHP	crisis	2017.07	Marawi crisis	Moro Islamic Liberation Front members used the ceasefire to repatriate civilians. However, ISIL-linked militants fired in areas occupied by government military forces. When the unilateral ceasefire expired, full-scale hostilities continued between government forces and militants.	0	1
PHP	crisis	2017.11-12	Marawi crisis	An Amnesty International report released on November 16, 2017, blamed the militants and government forces for widespread abuses, some of which amount to war crimes.	0	1
PKR	crisis	2015.03	India-Pakistan Conflict	India–Pakistan border skirmishes were a series of armed clashes and exchanges of gunfire between the Indian Border Security Force and the Pakistan Rangers in the disputed Kashmir region and the borders of Punjab. On 14th February 2015, A sixty-year-old villager was killed, and the event escalated the military tension.	1	1
PLN	crisis	2017.11	Ethnic purity	Around 60,000 people marched in Warsaw on Independence Day (November 12, 2017), some chanting anti-Semitic, anti-Muslim, and anti-gay slogans.	0	1
PLN	crisis	2019.12	Leave-EU proposal	The country's Supreme Court has warned that Poland could have to leave the European Union over the judicial reform proposal on December 17, 2019.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RON	crisis	2019.12	No-confidence vote	Romania's government lost a no-confidence vote, leading to the end of governance on October 10, 2019. A transitional government was expected to take over the country's governance until the next national election in 2020.	0	1
RUB	crisis	2017.03-04	Anti-corruption Protests	On March 26, 2017, roughly 60,000 people participated in anti-corruption protests across 80 Russian towns and cities. Hundreds of protesters were detained, including opposition leader Alexei Navalny and employees of the Anti-Corruption Foundation.	1	1
RUB	crisis	2017.11-12	Anti-corruption Protests	In Moscow, many police were present, and the Okhotny Ryad station was closed to avoid mass-scale protests. Police detained about 112 people on the night of November 6, 2017.	0	1
SAR	crisis	2017.11-12	Saudi Arabian purge	Crown Prince Mohammad bin Salman formed a committee to fight against corruption. Several prominent Saudi Arabian princes, government ministers, and business people were arrested in Saudi Arabia on November 4, 2017.	0	1
ARS	conflict	2017.12	Argentina Dirty War	Argentina's court granted house arrest to 88-year-old Miguel Etchecolatz, the former police officer who worked for the military dictatorship of the 1970s, for crimes against humanity in December 2017.	0	1
BRL	conflict	2017.12	Land conflicts	Deforestation is widespread in the Brazilian state of Rondônia, deep in the western Amazon rainforest. On December 1, 2017, a new investigation by Greenpeace revealed that deforestation of protected areas had risen in the state. Indigenous communities viewed deforestation as a massive threat to their disappearing homeland. And as budget cuts depleted resources to protect these communities, many were worried this conflict between industrialization and indigenous communities would worsen further.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
COP	conflict	2017.04	Sign of Peace Accord	The Revolutionary Armed Forces of Colombia (FARC) signed a peace accord in 2016 and demobilized its armed force in 2017. While 13,185 FARC members were formally demobilized, about 800 of them rejected the peace accord entirely and refused the demobilization.	1	1
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 17 November 2015 on the anniversary of the 1989 Velvet Revolution.	0	1
CZK	conflict	2017.12	Rising Czech populism	European far-right leaders gathered in Prague for a controversial conference likely to confront protests from groups who fear rising xenophobic populism in the Czech Republic.	1	1
IDR	conflict	2015.12	Papua conflict	The abundance of natural resources in West Papua generated continuing conflict, making it one of Asia's sorest spots regarding human rights violations. One article on December 15, 2015, discussed the human rights crisis in West Papua.	1	0
PKR	conflict	2016.01	Quetta suicide bombing	A suicide bomber detonated himself near a polio center near Quetta, Pakistan, killing at least 15 people and wounding another 25 in January 2016. Both Tehrik-i-Taliban Pakistan and Jaishul Islam organizations claimed responsibility.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
PKR	conflict	2019.02	India–Pakistan border skirmishes	In February 2019, Indian jets crossed the international border to conduct air strikes on an alleged JeM camp in the Khyber Pakhtunkhwa province of Pakistan.	0	1
PLN	conflict	2017.11	Ethnic purity conflict	Around 60,000 people marched in Warsaw on Independence Day (November 12, 2017), some chanting anti-Semitic, anti-Muslim, and anti-gay slogans.	1	1
RON	conflict	2019.03	Romania's politician jailed	Liviu Dragnea, the leader of Social Democratic Party (PSD), was sentenced to three and a half years of imprisonment for corruption on May 27, 2019.	2	1
RUB	conflict	2017.12	Syrian civil war	At the end of December 2017, the Russian government announced that its troops would be deployed to Syria permanently.	1	0
THB	conflict	2017.12	Thailand's southern conflict	One article on December 27, 2017, stated that 235 people died in 2017 due to clashes between the Muslim-Malay insurgents and Thai troops and police, according to numbers collected by Deep South Watch.	0	1
THB	conflict	2019.03	Senate composition controversy	Thailand's military government failed to create conditions for a free and fair national election in March 2019. The junta-appointed Senate hold roughly 50% of the total votes, severely undermining Thai citizens' right to choose their leaders.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
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.	0	1
UAH	conflict	2015.08	The conflict between Ukraine troops and pro-Russian separatists	News reports that a third member of Ukraine's national guard died from injuries after Monday's violent protests outside the parliament in Kyiv on August 31, 2015.	0	1
UAH	conflict	2016.01-02	Ukraine domestic conflict	According to BBC news in February 2016, Ukraine remained gripped by corruption, and little progress had been made in improving the economy. Conflicts in the Donbas with pro-Russian separatists further added economic uncertainties.	0	1
COP	instability	2016.07	Ceasefire deal	On June 23, 2016, the Colombian government and the Revolutionary Armed Forces of Colombia (FARC) rebels signed a historic ceasefire deal, bringing them closer to ending more than five decades of conflict.	0	0
ILS	instability	2017.08	Palestinian missile attack on Israel	Around 9 pm on August 8, 2015, one missile was launched from Gaza (a Palestinian city). It fell inside Israel in an open area near Ashkelon.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RUB	instability	2018.10	Amnesty researcher mock execution	On October 6, 2018, Oleg Kozlovsk, an Amnesty International researcher, was abducted, beaten, and threatened with death by people who identified themselves as officers of the local Center for Combating Extremism, a special police unit in Russia.	0	1
SAR	instability	2017.08	Qatar–Saudi Arabia diplomatic conflict	On August 24, 2017, Qatar announced that it would restore full diplomatic relations with Iran. As the diplomatic standoff reached its second year, Saudi Arabia announced it would build a canal and turn Qatar into an island.	0	0
Panel C: Other socioeconomic Events						
AED	crisis	2019.12	UAE economy first-ever drop	On December 5, 2017, Bloomberg reported that the U.A.E. economic output growth slowed, and unemployment surged.	0	1
AUD	crisis	2015.06	Migrant crisis	Australia detained any migrant and refugee trying to reach its shores, took them to offshore processing camps, and resettled them elsewhere.	0	0
BRL	crisis	2017.11-12	Sovereign credit rating downgraded	Brazil lost its investment-grade rating after Fitch became the second credit agency to downgrade the country's debt to junk grade on December 16, 2017. Fitch cited concerns about economic and political crises threatening to topple President Dilma Rousseff.	0	1
BRL	crisis	2019.12	Trump's steel tariffs	Trump imposed tariffs on Brazil on December 3, 2019.	0	0
COP	crisis	2015.08	Peso depreciation	As the petroleum industry in Colombia is an important contributor to the country's economy, the peso depreciated sharply against the U.S. dollar as the oil price declined.	0	1
GBP	crisis	2017.11	Homeless crisis	Meg Hillier, a British Labour and Co-operative politician, claimed that the government's approach to tackling the homelessness problem was an "abject failure" on December 20, 2017.	0	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
INR	crisis	2015.06	Indian milk crisis	Both private and cooperative dairies were rejecting milk from small dairy farmers in Andhra Pradesh. Meanwhile, milk procurement prices have been reduced, and farmers poured milk down the drain in June 2015.	0	0
INR	crisis	2019.12	Severe slowdown	The government made an ambitious policy goal for double-digit growth and propelled India into a $5 trillion economy by 2024-2025. However, India's gross domestic product (GDP) growth dropped to 4.5% in the third quarter of 2019, making the policy goal to be an implausible mission.	0	1
KES	crisis	2019.12	Kenya food crisis	In December 2019, Crisis and Stressed 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.	0	0
KES	crisis	2019.06	Drought in Africa	On June 15, 2019, a news article discussed precipitation shortages across eastern Africa, southern Africa, and the Horn of Africa; and altered another dire season for farmers. The drought would increase food prices and drive up the need for international aid to people who lived in the three regions.	1	0
PKR	crisis	2019.12	Balance of payments crisis	In December 2019, Pakistan implemented belt-tightening measures to ease a balance of payments crisis.	1	0
ZAR	crisis	2018.01	Cape Town water crisis	The Cape Town water crisis in South Africa was a severe water shortage in the Western Cape region, most notably affecting the City of Cape Town. In mid-January 2018, previous Cape Town Mayor Patricia de Lille announced that the City would be forced to shut off most of the municipal water supply if conditions continued.	1	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
ZAR	crisis	2019.12	South African energy crisis	The South African energy crisis, a period of national-level rolling blackouts as electricity shortage, destabilized the national power grid. South Africa experienced its worst energy crisis, and Load Shedding Stage 6 was activated for the first time in December 2019.	0	0
BRL	instability	2016.03	Zika virus	In February 2016, World Health Organisation declared a global public health emergency following an outbreak of the Zika virus in Brazil.	1	0
INR	instability	2016.02	Indian stock market crash	By 16 February 2016, the Bombay Stock Exchange (BSE) had seen a fall of 26% over the past eleven months, losing 1,607 points in four consecutive days.	0	1
Panel D: Irrelevant Events						
AED	scandal	2015.07	Ambassador 1MDB scandal	On June 30, 2017, the Wall Street Journal reported that companies connected to Yousef Al Otaiba, the United Arab Emirates ambassador, received $66 million allegedly misappropriated from 1Malaysia Development Berhad.	0	
AUD	scandal	2018.03-04	Ball-tampering scandal	A scandal surrounded the Australian national cricket team. In March 2018, television cameras caught Cameron Bancroft trying to rough up one side of the ball with sandpaper to make it swing in a match against South Africa at Newlands.	0	
CAD	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a “fraudulent device/software” in diesel engines that could cheat the emissions tests in the United States.	0	
KRW	scandal	2019.03	K-Pop sex scandal	Seungri (Lee Seung-Hyun), a former member of the South Korean band BIGBANG, appeared at the police station on March 14, 2019. He was questioned over the charges of facilitating prostitution services.	0	

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
MXN	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a “fraudulent device/software” in diesel engines that could cheat the emissions tests in the United States.	0
PKR	scandal	2015.08	Child sexual abuse scandal	On August 10, 2015, the parents of victims in a horrific child sexual abuse scandal said that the Pakistan police tried to downplay the scale of crimes committed.	0
PKR	scandal	2019.11	Spot-fixing scandal	Pakistan cricketer Mohammad Asif apologized for his involvement in a 2010 betting scandal and admitted his spot-fixing role.	0
RON	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a “fraudulent device/software” in diesel engines that could cheat the emissions tests in the United States.	0
SEK	scandal	2015.09	Swedish jet scandal	In September 2015, Financial Times revealed that many business ethical scandals in which executives enjoyed inappropriate perks in Sweden, such as hunting lodges, business jets, and reimbursing each others’ expenses.	0
SEK	scandal	2017.04	Swedish elk-hunting scandal	The chairman of Handelsbanken, often regarded as one of Europe’s most respected banks, has become the latest senior Swedish business figure caught up in the scandal over elk hunting hospitality.	0
SEK	scandal	2018.03	Swedish academy scandal	72-year-old Jean-Claude Arnault, the former artistic director of the cultural center Forum, was accused of sexual misconduct.	0
SEK	scandal	2018.12	Swedish academy scandal	In early December 2018, Jean-Claude Arnault was found guilty by a Stockholm court of rape against one woman and sentenced to two years and six months in prison.	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
VND	scandal	2019.03	Food safety scandal	Dozens of kindergarteners in the northern Vietnamese province of Bac Ninh have tested positive for pork tapeworm in less than a month. Their parents blamed dirty school meals for the mass infection of unprecedented scale in March 2019.	0
AUD	crisis	2019.12	Australia's bushfire crisis	Record-low rainfall contributed to severe bushfires that burned more than 5 million hectares.	0
CAD	crisis	2019.12	Climate crisis	Justin Trudeau's newly re-elected government will decide whether to approve the construction of the largest open-pit oil sands mine in Canadian history. If approved, the mine would be a huge environmental threat.	0
CHF	crisis	2017.11	Rohingya crisis	Switzerland urged joint efforts to resolve the Rohingya crisis on November 21, 2017.	0
PHP	crisis	2019.12	Christmas typhoon	Christmas Typhoon caused 20 death in the Philippines.	0
Panel E: Unknown Events					
ARS	scandal	2019.8			0
HRK	scandal	2015.01			1
ILS	scandal	2015.09			0
JPY	scandal	2016.03			0
SAR	scandal	2015.07			0
ZAR	scandal	2016.05			0
CHF	crisis	2019.12			0
JPY	crisis	2017.04			1
SEK	crisis	2019.12			0
SEK	crisis	2017.11-12			0
THB	crisis	2016.11			0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
CZK	conflict	2016.11-12			0
PHP	conflict	2018.08-09			1
PHP	conflict	2019.08-09			0
VND	conflict	2017.12	(best guess) Vietnam War		0
CHF	instability	2018.05			0
SEK	instability	2019.12			0
SEK	instability	2017.11-12			0
ZAR	conflict	2016.02			0
ZAR	conflict	2017.02			0
ZAR	conflict	2018.02			1
ZAR	conflict	2019.02			0
ZAR	conflict	2020.02			1

C For Online Publication: Limits of Arbitrage

In this section, we discuss various frictions in cryptocurrency trading. Price deviations can reflect the underlying cross-country Bitcoin demand only if the law of one price fails. We empirically give content to the sources of friction and provide a quantitative evaluation. 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 defined as 100 minus correlation (in percent) between the Bitcoin returns in local currency, and the Bitcoin U.S. dollar returns in a rolling window of eight weeks.

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

where Ret_c^{BTC} is the Bitcoin return in local currency and Ret_{USD}^{BTC} is the U.S. dollar return. A higher return asynchronization implies more disconnection with the international Bitcoin market, in other words, more friction to arbitrage.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%. We first characterize the relationship between return asynchronization and price deviation at the country level. First, Bitcoins are more expensive in markets with higher friction. Figure C.1 plots the relationship between the average return asynchronization and average price deviation by currency. One percentage point increase in asynchronization corresponds to an average 11.57 bps (*s.e.*=2.95, R-squared = 0.20) higher price deviation. A higher price premium can incentivize arbitragers to sell more Bitcoins to the country. Second, more frictions also correspond to a more volatile price. Figure C.2 checks a relationship between the average return asynchronization and the standard deviation of price deviation by currency. These two measures yield a 12.68% correlation (*s.e.*=2.05).

In the remaining section, we evaluate how different types of friction correlate with cross-country variation in return asychronization. Investors face various restrictions or costs on cross-country arbitrage, at least in the short run. An arbitrager needs to complete the following these steps to take advantage of the price difference across the market:

1. Convert the U.S. dollar into Bitcoin through a crypto-exchange;

2. Send Bitcoin from the exchange wallet to a private wallet;

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

4. Sell Bitcoin for local currency;
5. Transfer funds from a local crypto exchange to a local bank account;
6. Convert local currency back to the U.S. dollar and remove the money from 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.[59] We start with capital controls—the conventional explanation—then examine crypto-fiat liquidity, market segmentation, and legal risks.

C.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 the U.S. dollar. Simultaneously, as shown in Figure A.1, the 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, arbitragers would face more challenges when sending money out of the country or might not convert local currencies to the U.S. dollar at a desirable exchange rate. Following Fernández et al. (2016), we classify all countries into three categories: Open (least restrictive), Gate, and Wall (most restrictive). Small retail arbitragers face 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.[60]

Table C.1 correlates the average return asynchronization with the capital controls and retail transaction costs. Return asynchronization is higher in countries with more restrictive capital controls: 10.4% for 20 "Gate" countries and 14.9% for five "Wall" countries. However, as reported in Columns (1) and (2), no more than 11.54% of variation can be explained by the capital control measure. Moreover, we do not find retail transfer costs correlate with the return asynchronization, as shown in Columns (3) - (6). Our findings confirm that capital controls matter but do not explain such considerable variation in asynchronization.

[59] See: Makarov and Schoar (2019), Makarov and Schoar (2020), Yu and Zhang (2022), and Choi et al. (2022)

[60] Money transfer costs are only available for some money corridors from local countries to the United States. Thus, we use the transfer costs of corridors from the United States to other countries instead.

C.2 Insufficient Liquidity

But why do we see price deviations even in countries with the free capital flow? 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 was only 1,214 BTC in 2019, while the trading volume in U.S. dollar was 16,702,356 BTC.[61] Arbitragers either fail to find enough Bitcoin buyers in Sweden or cannot sell many Bitcoins without lowering the Sweden Krona price.

We explore whether the trading volume can explain the cross-country variation in return asynchronization. Figure C.3 plots the average return asynchronization and log Bitcoin trading volume in 2019. One unit increase in log volume predicts a 2.88 ($s.e.$=0.55) decrease in return asynchronization. The R-squared is 54.78%.

C.3 Laws and Regulations

In September 2017, China announced its plan to crack down on cryptocurrency exchanges, and Bitcoin trading volume in China plummeted by over 99%. Figure C.4 shows the rise of return asynchronization after the ban became effective in November.[62] 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 regulations 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. The most crucial dichotomy is whether cryptocurrency trading is legal or not. The United Arab Emirates, Pakistan, and Vietnam explicitly defined cryptocurrency as unlawful. Colombia, China, Indonesia, Pakistan, Saudi Arabia, and Thailand implicitly banned or announced policies against cryptocurrencies.[63]

[61] The real trading volume can be even lower than the data shows. **?** implies that crypto exchanges frequently use wash trading to fake volume.

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

[63] A standard implicit ban that targets crypto exchanges is to forbid domestic banks from opening bank accounts for crypto exchanges. Exchanges cannot receive fiat money from investors; thus, investors cannot easily trade through exchanges. There are many ways to circumvent the restrictions on bank accounts, such as working with foreign banks or building an OTC

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 enacted anti-money laundering laws specific to cryptocurrencies; Argentina, Brazil, the United Kingdom, Israel, Kenya, Mexico, Sweden, and South Africa issued anti-money laundering warnings. Argentina, Australia, Canada, Switzerland, the United Kingdom, Israel, Japan, Poland, Romania, Russia, Sweden, and South Africa proposed tax laws for cryptocurrency trading.[64]

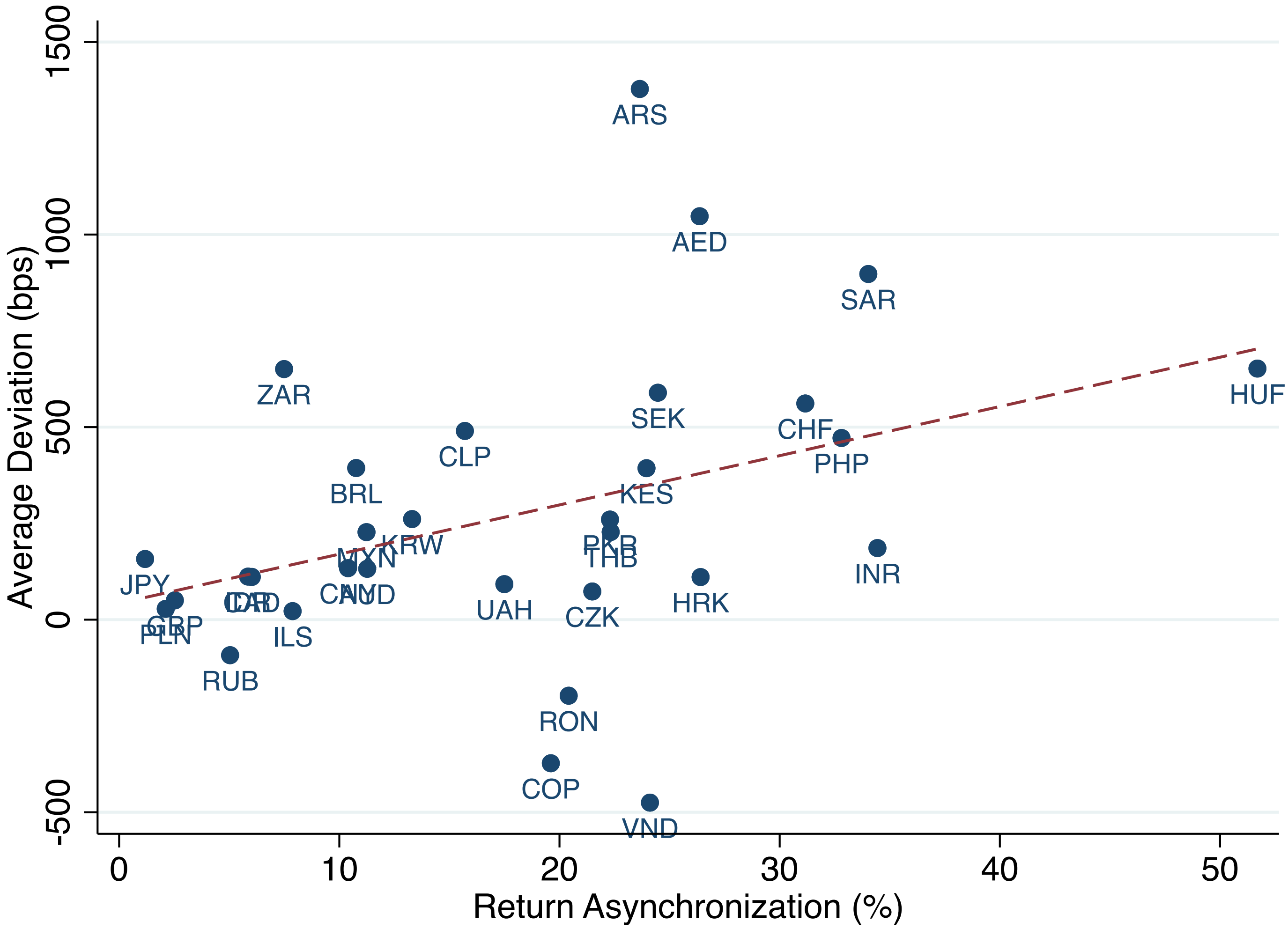
Table C.2 reports the relationship between return asynchronization and regulations. Of 31 countries, 6 countries do not impose cryptocurrency regulations by 2020. Column (1) implies the 6 unregulated countries experience 6.05% ($s.e.$ = 4.42%) higher return asynchronization on average. Within the 25 countries with regulations, Column (2) shows cryptocurrency bans (implicit and explicit pooled) raise return asynchronization by 5.89% ($s.e.$= 1.80%) 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 6.55% ($s.e.$= 3.79%) and 2.42% ($s.e.$ = 3.96%), respectively. Figure C.5 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.[65]

market. Note that the OTC platforms are hard to ban as OTC platforms do not need to interact with the local banking system. Investors on OTC platforms send fiat currency to their trading counterpart's bank account directly. Thus, we still find trading activities even after countries banned Bitcoin.

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

[65]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/.

Figure C.1: Return asynchronization and average Bitcoin price deviation

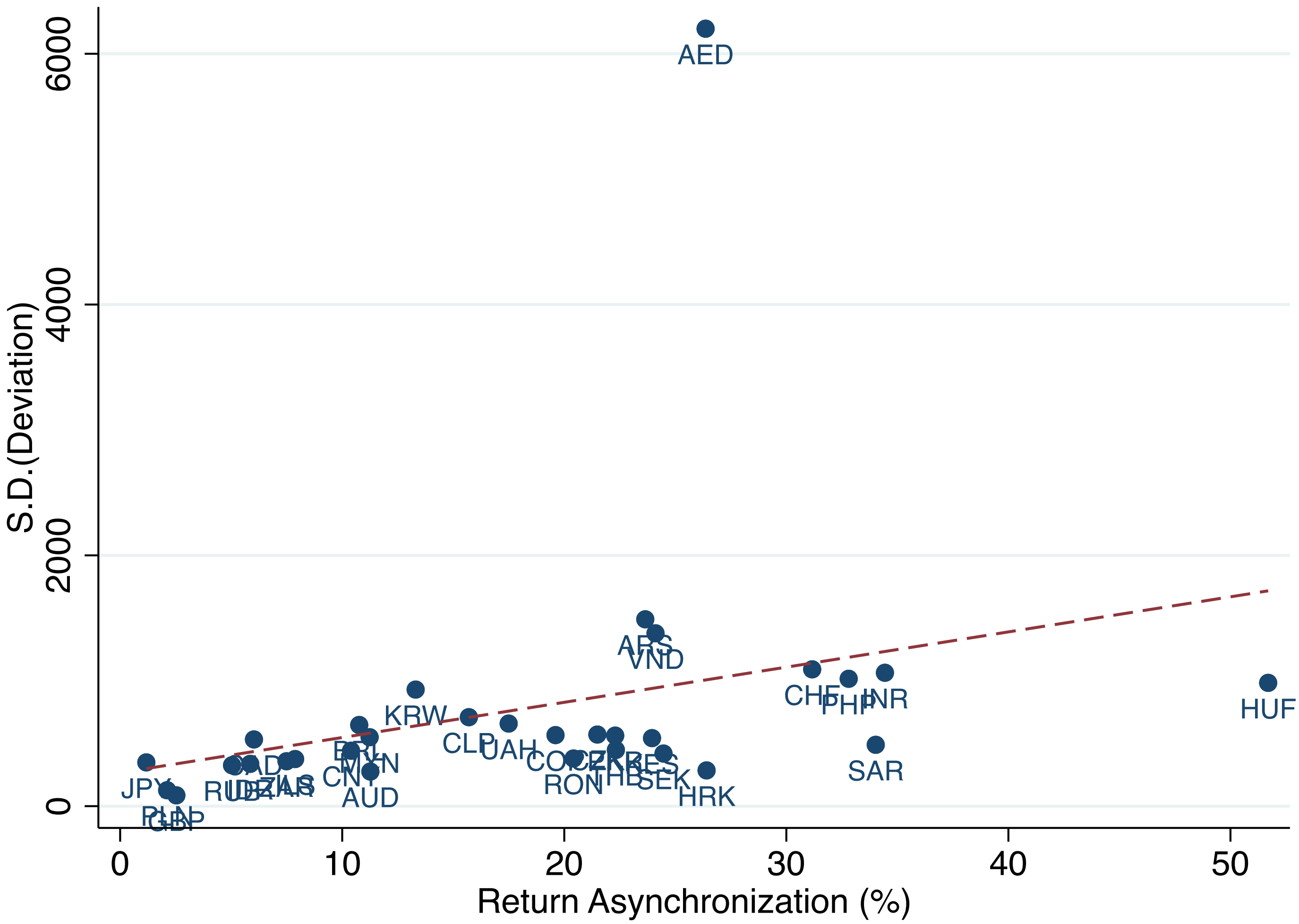


Notes: This figure shows the relationship between the average return asynchronization and the average price deviation by currency.

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

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

Figure C.2: Return asynchronization and standard deviations of price deviations

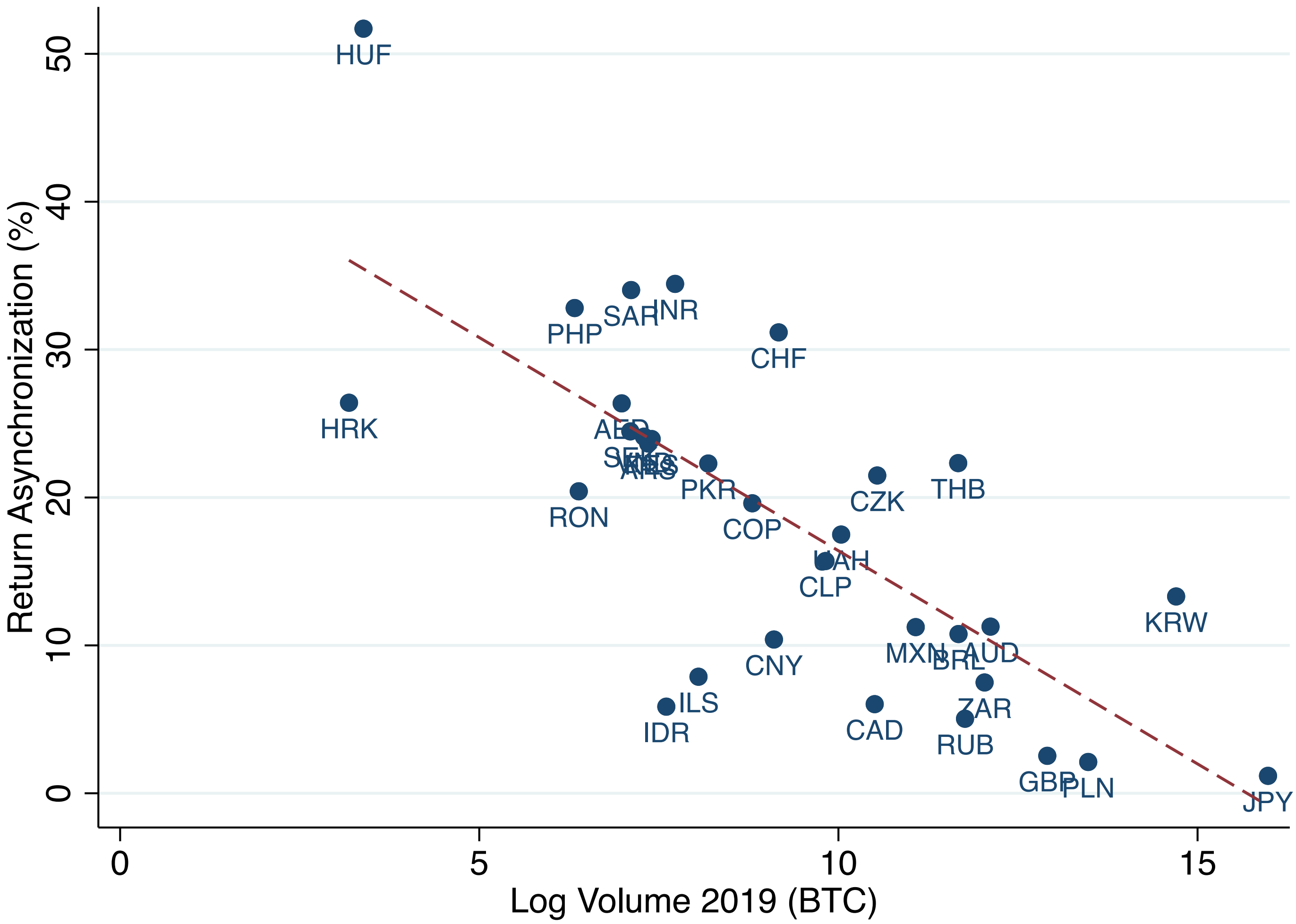


Notes: This figure shows the positive relationship between the average return asynchronization and the standard deviation of price deviations by currency.

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

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

Figure C.3: Return asynchronization and liquidity

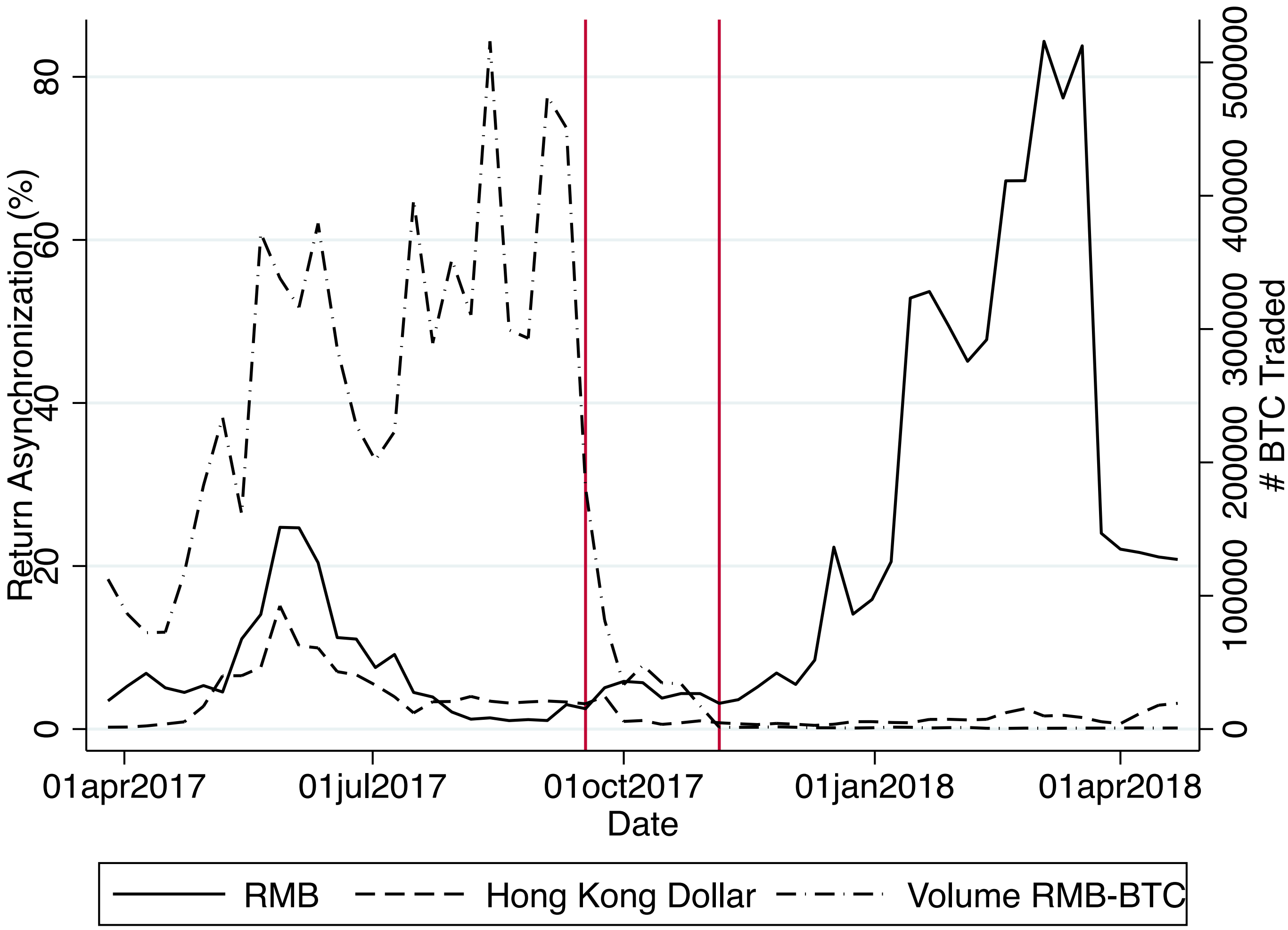


Notes: This figure plots the average return asynchronization and log trading volume in 2019.

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

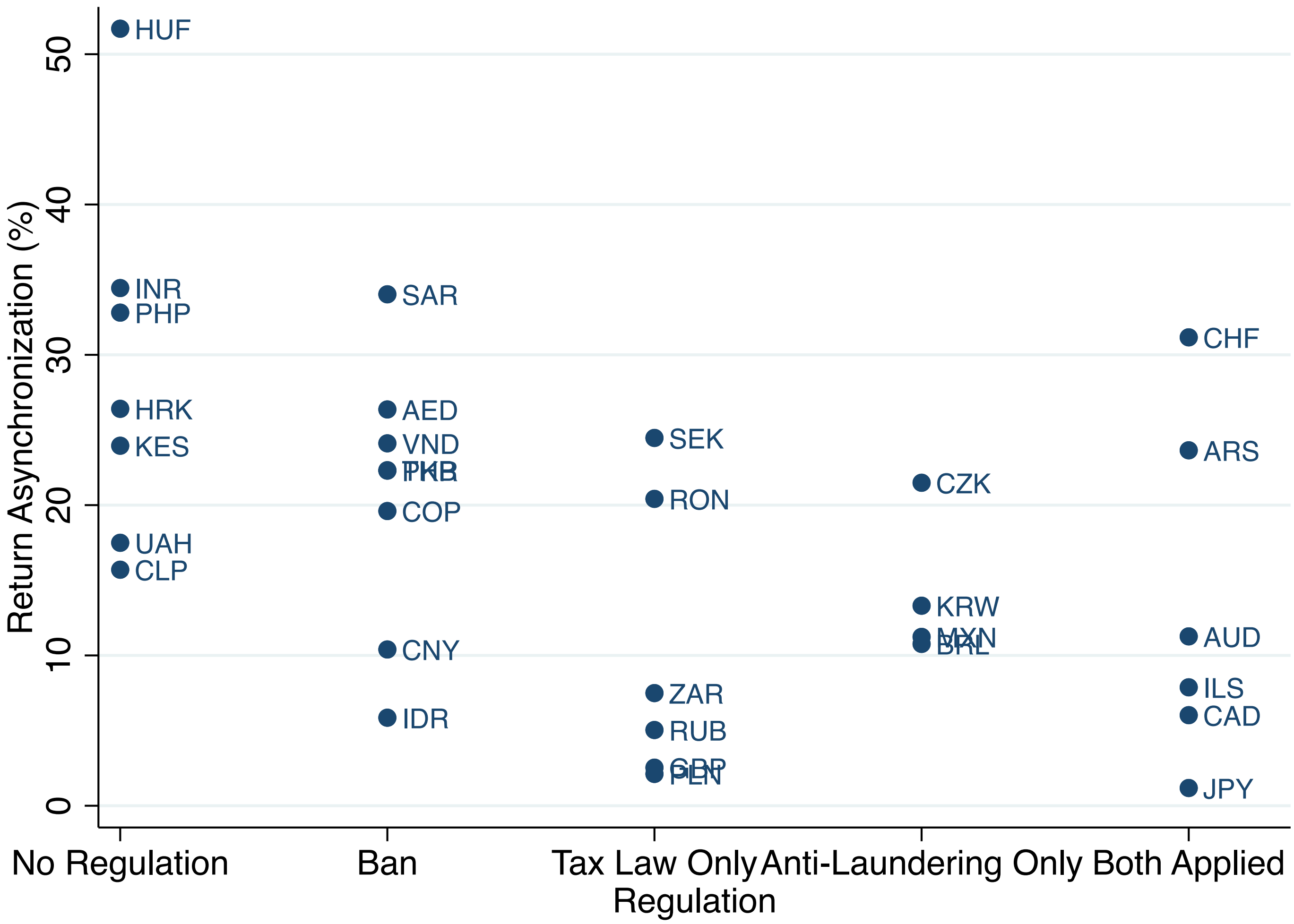
where $\overline{Asyn_c}$ is the average return asynchronization of country c, and Log_Vol_c is the log number of Bitcoins traded in 2019.

Figure C.4: Return asynchronization before and after China Ban



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, 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 to reduce financial risks. The weekly trading volume (dash-dotted line) of Bitcoin drops from 450885.96 (Sep 10, 2017) to 33387.74 (Oct 1, 2017), to 1373.24 (Nov 5, 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 C.5: 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.”

Table C.1: Return asynchronization and capital controls

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 the "Open" category, 2 to the "Gate" category, and 3 to the "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. Columns (3) and (4) report the results based on data from Monito.com, and Columns (5) - (6) report the results based on data from the World Bank remittance survey. The exchange rate margin refers to the markup paid to the service provider per unit of funds transferred. The transaction fee refers to the fixed cost per transaction the service provider charges.

$$\overline{Asyn_c} = \beta X_c + \gamma + \epsilon_c$$

where $\overline{Asyn_c}$ is the average return asynchronization in country c, and X_c refers to capital control or retail transfer cost. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Return Asynchronization					
	Capital Controls		Retail Transfer Costs			
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Controls	7.240**					
	(3.268)					
i.Gate		10.352*				
		(5.533)				
i.Wall		14.936**				
		(6.530)				
Exchange Rate Margin			0.694		-2.422	
			(2.091)		(2.814)	
Transaction Fee				-0.591		-0.254
				(0.891)		(0.396)
R-squared	11.54%	12.83%	0.49%	0.93%	6.62%	3.00%
# Currencies	31	31	29	29	12	12

Table C.2: Return asynchronization and regulations

This table reports the relationship between return asynchronization and regulations. We classify the regulatory status into four categories. "Regulate or not" dummy is one of the countries that have any specific regulation for cryptocurrency; otherwise, zero. "Legal Status" dummy is one if regulators ban cryptocurrency; otherwise, zero. The "Tax Laws" dummy is one if tax laws apply to cryptocurrency; otherwise, zero. "Anti-Money Laundering" dummy is one of the countries that 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. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Return Asynchronization (%)			
	(1)	(2)	(3)	(4)
Regulateornot	-6.052			
	(4.423)			
LegalStatus		5.892***		
		(1.796)		
TaxLaws			-6.546*	
			(3.788)	
Anti-MoneyLaundering				-2.421
				(3.964)
#Currencies	31	24	24	24

D For Online Publication: Law and Regulations

We collect data on 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 guided the tax treatment of cryptocurrencies in May 2016, and Australian Taxation Office (ATO) followed with a set of actions. Regarding anti-money laundering and counterterrorism financing (AML/CTF), the government introduced a bill in Parliament in August 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 virtual currencies’ trading and custody.
CAD	0	1	3		Mar, 2017	Jun, 2014	On June 19, 2014, the Governor General of Canada consented to Bill C-31, which includes amendments to Canada’s Proceeds of Crime (Money Laundering) and the Terrorist Financing Act. The new law treated virtual currencies, including Bitcoin, as “money service businesses” for the anti-money laundering law.

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 June 2017 circular that bitcoin is not a currency in Colombia and therefore may not be considered legal tender susceptible to canceling 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 November 14 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.
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 year.
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 Theory Appendix: Bitcoin and Local Risky Weights

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. The subscript e refers to the state of government exploitation occuring; ne refers to the state of exploitation not happening.

$$\begin{aligned}
\max_{\pi_{L,t},\pi_{B,t}} logE_t[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}] &= \max_{\pi_{L,t},\pi_{B,t}} log\{E[p\frac{W_e^{1-\gamma}}{1-\gamma} + (1-p)\frac{W_{ne}^{1-\gamma}}{1-\gamma}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} log\{E_t[pe^{(1-\gamma)w_{t+1,e}} + (1-p)e^{(1-\gamma)w_{t+1,ne}}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} log\{E_t[pe^{(1-\gamma)r_{p,t+1,e}} + (1-p)e^{(1-\gamma)r_{p,t+1,ne}}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,ne}}[1-p+pe^{(1-\gamma)(r_{p,t+1,e}-r_{p,t+1,ne})}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,ne}}[1-p+pe^{(1-\gamma)\pi_{L,t}\kappa}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} logE_t e^{(1-\gamma)r_{p,t+1,ne}} + log\{E_t[1-p+pe^{(1-\gamma)\pi_{L,t}\kappa}]\} \\
&= \max_{\pi_{L,t},\pi_{B,t}} logE_t e^{(1-\gamma)r_{p,t+1,ne}} + log\{E_t[1-p+pe^{(1-\gamma)\pi_{L,t}\kappa}]\}
\end{aligned}$$

In the derivation, we use $w_{t+1,ne} = r_{p,t+1,ne}+w_t$, $w_{t+1,e} = r_{p,t+1,e}+w_t$, and the difference between portfolio returns in the exploitation and non-exploitation states can be derived with the following approximations: Firstly, we construct a portfolio using local risky asset and Bitcoin. The return of the portfolio is:

$$r_{LB,t+1,ne} \approx \frac{\pi_{L,t}}{\pi_{P,t}}r_L + \frac{\pi_{B,t}}{\pi_{P,t}}r_B + \frac{1}{2}\frac{\pi_{L,t}\pi_{B,t}}{\pi_{P,t}^2}(\sigma_L^2 + \sigma_B^2 - 2\rho\sigma_L\sigma_B)$$

where, $\pi_{P,t} = \pi_{L,t} + \pi_{B,t}$.

Then, we can calculate the return of the portfolio with the portfolio constructed above and risk-free asset:

$$r_{p,t+1,ne} - r_f \approx \pi_{P,t}(r_{LB,t+1,ne} - r_f) + \frac{1}{2}\pi_{P,t}(1-\pi_{P,t})\sigma_P$$

$$r_{p,t+1,ne} - r_f \approx \pi_{P,t}(r_{LB,t+1,ne} + \kappa - r_f) + \frac{1}{2}\pi_{P,t}(1-\pi_{P,t})\sigma_P$$

$$r_{p,t+1,e} - r_{p,t+1,ne} = \pi_{L,t}\kappa$$

where, $\sigma_P = \frac{\pi_{L,t}^2}{\pi_{P,t}^2}\sigma_L^2 + \frac{\pi_{B,t}^2}{\pi_{P,t}^2}\sigma_B^2 - 2\frac{\pi_{L,t}\pi_{B,t}}{\pi_{P,t}^2}\rho\sigma_L\sigma_B$

Therefore, the maximization problem becomes:

$$\max_{\pi_{L,t},\pi_{B,t}} \underbrace{\pi_{L,t}(r_L - r_f) + \pi_{B,t}(r_B - r_f) + \frac{1}{2}\pi_{L,t}\sigma_L^2 + \frac{1}{2}\pi_{B,t}\sigma_B^2 - \frac{\gamma}{2}(\pi_{L,t}^2\sigma_L^2 + \pi_{B,t}^2\sigma_B^2 + 2\frac{\pi_{L,t}\pi_{B,t}}{\pi_{P,t}^2}\rho\sigma_L\sigma_B)}_{\text{Financial Component}} + \underbrace{p\pi_{L,t}\kappa}_{\text{Trust Component}}$$

The first part is the optimization problem, which is purely based on the financial component, and the second part comes from the distrust loss. Using the FOCs for $\pi_{L,t}$ and $\pi_{B,t}$, we can solve the optimal investment in the local risky asset and Bitcoin:

$$\pi_B = \frac{1}{\gamma\sigma_B^2}\frac{\sigma_L^2\tilde{\mu_B} - \rho\sigma_L\sigma_B\tilde{\mu_L}}{(1-\rho^2)\sigma_L^2}$$

$$\pi_L = \frac{1}{\gamma\sigma_B^2}\frac{\sigma_B^2\tilde{\mu_L} - \rho\sigma_L\sigma_B\tilde{\mu_B}}{(1-\rho^2)\sigma_L^2}$$

where $\tilde{\mu_B} = \mu_B + \frac{1}{2}\sigma_B^2 - r_f$, $\tilde{\mu_L} = \mu_L - r_f + p\kappa + \frac{1}{2}\sigma_L^2$