Essays on Fintech, Finance, and Development Economics

HARVARD UNIVERSITY
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Essays on Fintech, Finance, and Development Economics

A dissertation presented

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Essays on Fintech, Finance, and Development Economics

Abstract

The first chapter uses violations of the law of one price of Bitcoin to uncover sources of demand for cryptocurrency. In line with Hayek, we show that distrust breeds demand. We proxy Bitcoin demand with transitory price deviations---Bitcoin prices in a local currency, converted into dollars, relative to the average worldwide dollar Bitcoin prices. A simple portfolio choice model elucidates several predictions we find in the data. Price deviations rise when 1) perceptions of institutional failures grow, 2) crypto-trading frictions increase, and 3) cryptocurrency prices rally. These price responses are stronger in countries where people express more distrust in others.

The second chapter asks whether massive online retailers such as Amazon and Alibaba issue digital tokens that potentially compete with bank debit accounts? There is a long history of trading stamps and loyalty points, but new technologies are poised to sharply raise the significance of redeemable assets as a store of value. Here we develop a simple stylized model of redeemable tokens that can be used to study sales and pricing strategies for issuing tokens, including ICOs. Our central finding is that platforms can generally earn higher revenues by making tokens non-tradable unless they can generate a sufficiently high outside-platform convenience yield.

The third chapter tests neoclassical theory predicts convergence towards steady-state income. Empirical tests of convergence in the 1990s found that conditioning on such correlates of growth mattered: unconditionally the norm was divergence. We revisit these empirical tests of convergence with 25 years of additional data. While the recent literature on institutions emphasizes historical origins and persistence, we find substantial change. First, there has been a trend towards unconditional convergence since 1990, leading to convergence since 2000, driven both by faster catch-up growth and slower growth at the frontier. Second, many of the correlates of growth and income - human capital, policies, institutions, and culture - have converged substantially in the same period, in the direction associated with higher income. As such, unconditional convergence has converged towards conditional convergence.

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Yang You

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Chapter 1

1 Distrust and Cryptocurrency

This paper uses violations of the law of one price of Bitcoin to uncover sources of demand for cryptocurrency. In line with Hayek, we show that distrust breeds demand. We proxy Bitcoin demand with transitory price deviations—Bitcoin prices in a local currency, converted into dollars, relative to the average worldwide dollar Bitcoin prices. A simple portfolio choice model elucidates several predictions we find in the data. Price deviations rise when 1) perceptions of institutional failures grow, 2) crypto-trading frictions increase, and 3) cryptocurrency prices rally. These price responses are stronger in countries where people express more distrust in others.

1.1 Introduction

In the famous book *The Denationalization of Money*, Hayek (1978) argues that distrust in government and central banks justifies the demand for denationalized private money. As many have argued, Bitcoin is perceived as a safe-haven asset, much like gold, that provides algorithmic trust governed by decentralized blockchains and satisfies investors' safety needs. Does distrust drive the demand for cryptocurrency? We use the trust measure in the Global Preference Survey, which asked respondents whether they assume that other people only have the best intentions.[1] Our paper offers empirical support for the distrust argument.

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

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

that distrust plays a central role in explaining cross-country Bitcoin demand.

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

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

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

bps in low-trust countries. In reaction to the same unit change in the friction, Bitcoin prices rise three times more in low-trust countries than in high-trust countries.

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

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

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

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

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

Our paper is organized as follows. Section 1.2 documents the motivating facts: crypto-trading is more active in low-trust countries, and pervasive price deviations enable the opportunity to identify cross-country Bitcoin demand. Section 1.3 provides a theoretical framework of trust in portfolio choice and makes testable predictions. Section 1.4 brings empirical predictions to the Bitcoin trading data, investigates the determinants of price deviations, and highlights the importance of distrust on Bitcoin demand. Section 1.5 investigates the limits of arbitrage in crypto-trading. Section 1.6 explores the micro foundations in trust, validates the model assumption, and discusses implications in investment strategies. Section 1.7 concludes.

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

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

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

1.2 Motivating Facts

1.2.1 Trust and Bitcoin Trading

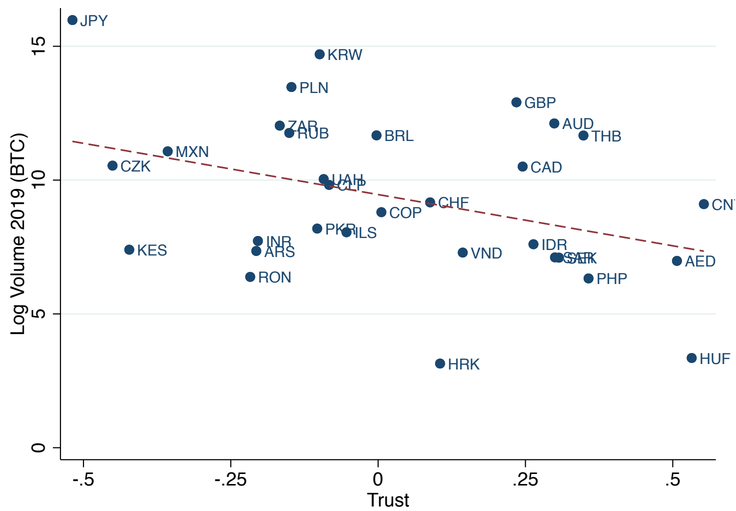
We first show that Bitcoin trading is more active in countries with lower levels of trust.[5] The trust measure is from the Global Preference Survey (GPS), which asks respondents whether they assume that other people only have the best intentions.[6] In our sample, Japan (-0.51873) is the lowest trust country, and China (0.55281) is the highest trust country. Figure 1 Panel A shows the correlation between the trust level and log numbers of Bitcoins traded in the country's currency in 2019. Table 1 Column (1) reports that the slope is -3.83 (t=-2.18), which translates into 4.1 times if the trust level moves from the minimum to the maximum level.[7] We add more controls: population size, GDP per capita in Column (2), cryptocurrency regulations in Column (3), and capital controls and financial credit in Column (4).[8] The coefficient before *Trust* becomes larger with more robust statistical power. Columns (5)-(8) report the same set of regressions with Bitcoin traded per capita as the dependent variable. The negative relationship still holds.

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

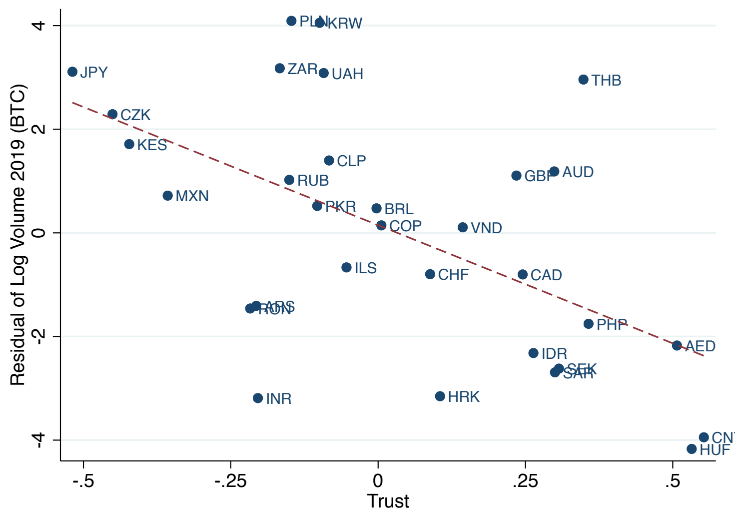
[6]GPS survey shows that this question was a strong predictor of trusting behavior in incentivized trust games, in the survey design stage.

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

[8]Section 1.5.4 provides detailed discussions on regulation variables.



Panel A: Raw Volume



Panel B: Residual Volume

Figure 1: Bitcoin Trading Volume and Trust Level

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

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

Then, we examine how much cross-country variation in Bitcoin's popularity can be ex-

Table 1: Bitcoin Trading Volume and Trust Level

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

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

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

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

plained by the trust.[9] As total Bitcoin trading volume correlates with the population size and economic prosperity, we define the residual log trading volume $\widehat{Log\_Vol_c}$ as the unexplained error term orthogonal to population size (Pop_c) and GDP per capita (GDP_c). $\widehat{Log\_Vol_c}$ is estimated from the following regression:

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

Figure 1 Panel B plots the correlation between the trust level and residual log volume. The negative slope increases to -4.56 (t=-3.62). Trust can explain 31.14% variation in the residual trading volume.[10]

1.2.2 Deviations from the Law of One Price

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

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

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

$Prc_{c,t}$ is the price in the local currency of country c, and $Exchange_{c-USD,t}$ is the exchange

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

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

rate from Bloomberg.[11] We obtain 5-year (Jan. 2015 - Jan. 2020) cryptocurrency prices and trading volumes from CryptoCompare.[12] The deviation should equal one if the law of one price holds perfectly.

Bitcoin price deviations can be astoundingly large. Figure A.1 plots the price deviations in Argentina and the United Kingdom from 2015 to 2020. During the 2018 Argentine monetary crisis, the maximum price gap in that country reached 37.14% in January. On the same date, the price difference was only 2.16% in the United Kingdom. Compared to the UK, Argentine Bitcoin prices are also much higher and volatile over time. Argentina is the country with the most expensive Bitcoins; it is 12.07% more expensive on average to buy Bitcoins there than in the US. Colombia is the country with the cheapest Bitcoins; they are 3.51% cheaper than US Bitcoins on average. Table 5 Panel A presents the summary statistics of price deviations across 31 countries in our sample. The average price deviation across all countries is 3.26%, and the standard deviation is 13.25%.

1.3 Theory

This section develops a simple model to introduce trust in the portfolio choice framework formally. We derive a closed-form solution for price deviations as a function of trust and other factors. With the model, we can deliver a set of testable empirical predictions about Bitcoin price deviations to understand more about what elements affect the Bitcoin demand and how they interact with country-level distrust. In our model, distrust is defined as the perceived probability of being cheated. Investors suffer from financial loss when cheating happens.[13] Distrust is exogenous and time-invariant for a given country.

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

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

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

1.3.1 Model Setup

Assets

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

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

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

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

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

in their home countries. Empirically, we validate that $\rho > 0$ in Section 1.6.3.

Investors

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

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

Supply Curve

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

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

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

κ is the price elasticity relative to the excess demand.[17] κ is the parameter that reflects the limits of arbitrage discussed in the Section 1.5. When market friction increases, a higher κ indicates a larger price change in response to the same demand shock. We assume no

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

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

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

supply shocks in the economy; that is, the demand side drives price deviation changes only.

1.3.2 Asset Allocation and Trust

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

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

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

Comments: Distrust leads to under-investment, even non-participation in the domestic risky asset market. The numerator (approximately) shrinks by the average loss from cheating: $(\bar{b} + \frac{1}{2}\sigma_b^2) \approx log(E(B)) < 0$. B is universally smaller than one by the definition of cheating. $log(E(B)) \approx E(B) - 1$ if B is not far below 1. Investors choose not to invest if domestic excess return $\mu_L - rf_L + \frac{1}{2}\sigma_L^2$ is lower than the expected loss from cheating $plog(E(B))$. Trust risk $p\sigma_b^2$ inflates the denominator, thus further lowering exposure to domestic risky assets.

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

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

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

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

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

[18] See Appendix B.1 for math derivation.
[19] See Appendix B.2 for math derivation.

the first-order approximation with respect to p.

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

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

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

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

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

1.3.3 Empirical Predictions

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

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

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

We make empirical predictions on the determinant factors in price deviations and focus on the heterogeneous responses by country-level distrust. Figure 2 shows the shifts of supply and demand curves as a graphic illustration for the following predictions.

Prediction 1: Information on institutional failures expands price deviation.

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

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

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

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

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

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

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

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

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

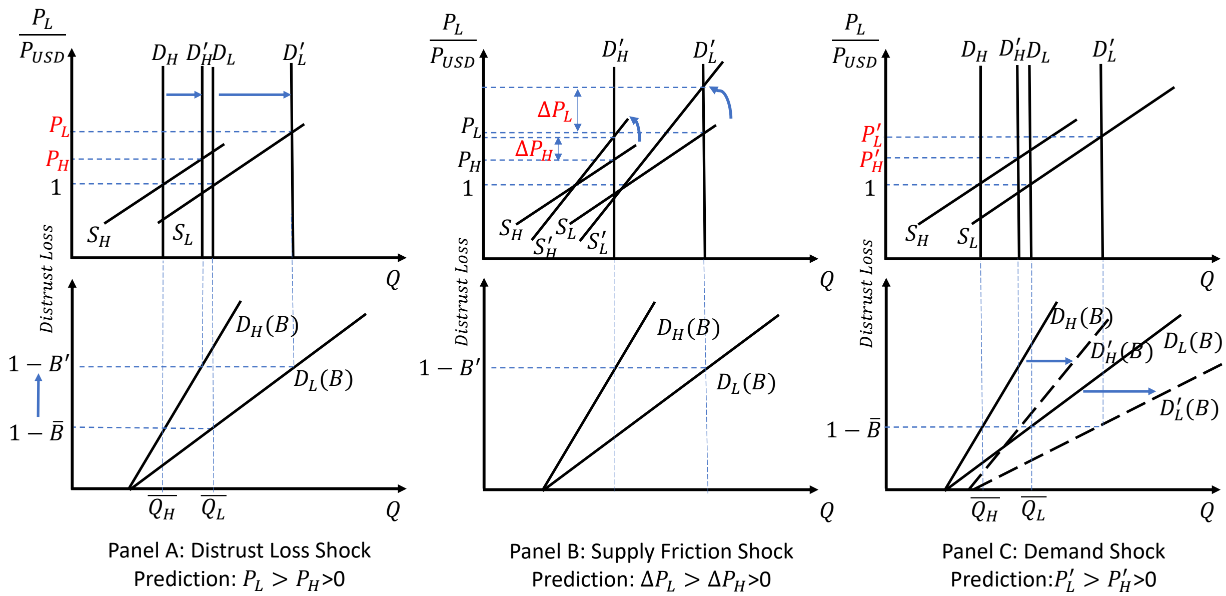


Figure 2: Conceptual Framework: Demand and Supply Curve

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

1.4 Empirical Tests

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

1.4.1 Data Description

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

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

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

1.4.2 Institutional Failures and Trust

We start with Prediction 1. Google trend indices on "Conflict", "Crisis", "Instability", and "Scandal" to capture people's concerns about domestic institutional failures (b). To smooth out times series, we compute $GT_{c,t}$ as a discounted sum of Google search indices in the past eight weeks with a discount factor of 0.8.[23]

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

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

[22]Canadian stocks are from Compustat North America.

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

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

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

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

We regress price deviations on cumulative Google search indices one by one. To set a high bar for statistical significance, we cluster standard errors at the currency level (31 clusters) and adjust for heteroskedasticity in all regressions throughout the paper. Table 2 reports the results of the following regression:

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

The price deviation expands by 2.68 bps (t = 2.71), 1.32 bps (t = 2.07), 2.13 bps (t = 2.38), 2.01 bps (t = 2.81) when the search indices of "Conflict," "Crisis," "Instability," and "Scandal" rise by one unit, respectively. Scaled by standard deviations (s.d.) of indices, one s.d. move in cumulative Google searches correspond to a 1.74%, 0.78%, 1.44%, and 1.10% price deviation change, respectively. Investors buy more denationalized assets when they are more concerned about the risks of fragile institutions.[24]

Table 3 reports the impact of institutional failures on growth in attention to Bitcoin and trading volume. Column (1) shows that if a Google search for "Conflict" increases by one unit, the Bitcoin Google searches and Bitcoin trading volume increase by 10.0% (t = 4.52) and 11.1% (t=3.31), respectively. Columns (2) - (4) show similar results for the other three

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

Table 2: Price Deviation Response to Institutional Failures

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

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

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

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

keywords.[25,26]

Before moving forward, we manually check the real events behind the Google search spikes. Table A.3 gives some examples of institutional disruptions that correspond to Google search spikes, including military conflicts, sovereign credit downgrades, monetary system crisis, political and corruption scandals. Appendix **??** reports the event searching for all 121 Google search spikes. We can identify 95 events, while other the other 26 peaks cannot be matched with any news. 78 events, out of 95, are directly related to local institutions or politics. Almost no domestic search spike links to international news or events in other countries.[27]

Then, to test Prediction 2, we examine the role of trust in explaining the price response heterogeneity across countries. Based on the trust score from the Global Preference Survey,

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

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

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

Table 3: Attention to Bitcoin and Trading Volume

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

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

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

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

we divide the countries in our sample into three groups: 11 high-trust countries ($Trust \in [0.2, 1)$), 9 medium-trust countries ($Trust \in [-0.1, 0.2)$), and 11 low-trust countries ($Trust \in [-1, -0.1)$). In addition, we define the variable $Distrust$ as

$$Distrust = 1 - Trust$$

Table 4 Columns (2) - (4) report the regression results in Eq.(1) by country category. For the keyword "Crisis" one unit increase in the Google search results predicts the price deviation increases by 4.52 bps (t = 2.70) and 4.59 bps (t = 2.00) in medium-trust and low-trust countries, but almost no impact (-0.31 bps t = -0.47) in high-trust countries. In Column (5), we include the interaction term for cumulative Google search and $Distrust$, and run the following regression:

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

Table 4: Price Deviation Response to Google Trend by Trust

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

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

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

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

The coefficient β_2, which captures how the price response varies across the spectrum of trust, is 8.53 ($t = 2.95$). It is consistent with the results in Columns (2) - (4) that societies with lower trust levels are prone to chase cryptocurrencies more when concerns about institutions exacerbate. Table A.7 presents the results for the other three keywords ("Crisis," "Instability," and "Scandal") and shows a similar pattern.[28]

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

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

scores.[29] Table A.8 reports the horse-racing regressions:

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

Column (1) reports the result of the original specification (as in Table 4 Column (5)), and Columns (2) - (6) show the horse-racing results with the five co-variates. The rule of law takes the coefficient down the most, from 8.53 ($t = 2.95$) to 4.52 ($t = 4.10$). The statistical significance slightly increases, although the coefficient magnitude typically slips after controlling country features. The horsing-racing regressions confirms that distrust delivers unique explanatory power and cannot be easily substituted.

1.4.3 Crypto-market Frictions

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

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

where Ret_c^{BTC} is the Bitcoin return in local currency and Ret_{USD}^{BTC} is the USD return. A higher return asynchronization implies more disconnection with the international Bitcoin trading market, in other words, more frictions to arbitrage.[30] Table 5 Panel A reports

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

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

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

Table 6 reports regressions of price deviations on the return asynchronization. Column (1) reports the results for all countries. In the full sample, deviation is boosted by 8.55 ($t =$ 4.35) bps if return asynchronization increases by one percent. Columns (2) - (4) show the heterogeneity among countries with different trust levels. In high-trust countries, medium-trust countries, and low-trust countries, one percent increase in return asynchronization corresponds to 4.27 bps ($t = 3.73$), 7.63 bps ($t = 1.94$), 13.92 bps ($t = 3.35$) appreciation in price deviation. The coefficients increase monotonically: low-trust countries respond three times more aggressively than high-trust countries.

Table 6 also reports the mean and standard deviation of return asynchronization for each country group. The standard deviations from high to low-trust group are 33.41%, 32.98%, and 31.88%, and imply 1.43%, 2.52% and 4.44% price response to a one standard-deviation change in return asynchronization.

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

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

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

1.4.4 Risk Appetite

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

Table 5: Summary Statistics

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

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

Table 6: Price Deviation Response to Market Friction

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

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

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

at least partially, derive from excess buy-in, and vice versa.

Table 7 reports the results of the regression of local price deviations on the past Bitcoin returns.

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

Column (1) shows that one percent increase in past eight-week return leads to 1.19 bps ($t = 2.75$) increase in the price deviation on average. Columns (2) - (4) show the estimate by trust level: 0.43 bps ($t = 0.55$) in high-trust countries, 1.56 ($t = 1.75$) in medium-trust countries, and 1.66 ($t = 2.76$) bps in low-trust countries. The effects of risk appetite on local price deviations are mainly concentrated in medium and low-trust countries as well. The coefficient of interaction term in Column (5) is 3.11 ($t = 2.15$).[31]

We further study the impact of stock market returns (value-weighted) to explore the

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

Table 7: Price Deviation Response to Bitcoin Return

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

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

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

cross-country variation in risk appetite changes. $Ret^{Stock}_{c,t-9\to t-1}$ refers to the log cumulative returns over the past eight weeks. Table 8 Columns (1) - (4) report the results:

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

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

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

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

Table 8: Price Deviation Response to Local Stock Return

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

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

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

1.4.5 Distrust Loss Elasticity

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

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

To make elasticity χ interpretable, we normalize price deviation, Google trend, and return asynchronization to a standard normal distribution for each country, and linearly re-scale distrust to [0,1].[32] χ represents the cryptocurrency demand response to one s.d. move in perceived loss from distrust under a conceptual environment with the highest distrust and perfect isolation from the US crypto-market (return asyn. = 100%).

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

Table 9 reports the elasticity estimation with the four Google search keywords. "Conflict" yields the highest estimate — One s.d. cheating loss corresponds to 0.62 (t = 2.20) s.d. demand increase in Bitcoins. "Instability" gives a similar estimate of 0.58 (t = 1.99), while the "Crisis" and "Scandal" estimates are relatively smaller at 0.47 (t = 1.40) and 0.33 (t=0.78), respectively. The statistical power is limited as we include four interaction terms in the specification; and we set a high bar for statistical significance—standard errors are clustered by currency and heteroskedasticity is adjusted. χ estimates, ranging from 0.33 to 0.62, are positive, thus broadly consistent with Prediction 5.

Table 9: Distrust Loss Elasticity Estimation

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

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

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

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

1.5 Limits of Arbitrage

Our identification of Bitcoin demand entirely relies on the law of one price violations in Bitcoin trading. Investors must face limits of arbitrage, at least in the short run, so that transitory price deviations can exist in the data. Moreover, we use return asychronization—the quantitative measure of frictions' magnitude—as the slope of the Bitcoin supply curve; however, no prior research investigates why return asychronization is exceptionally high in some countries (e.g., Saudi Arabia) but very low in other countries (e.g., Japan). This section examines different types of frictions in the Bitcoin arbitrage and evaluates how these frictions explain the cross-country variation in return asychronization.

An arbitrager needs to proceed with the following these steps to take advantage of the price difference:

1. Convert US dollar into Bitcoin;

2. Send Bitcoin from exchange wallet to private wallet;

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

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

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

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

Many barriers can arise in this procedure and prevent arbitragers from acting; thus, leading to a positive-sloping Bitcoin supply curve in the short run. It is often argued in the literature that capital controls (Step 6) are the primary reason for the price deviations across countries in the literature.[33] Our results imply that capital controls can only explain 13% of cross-country variation in return asynchronization. The frictions in trading between cryptocurrency and fiat money play a more critical role in the short horizon. In the following sections, we first investigate capital controls — the conventional explanation — then examine crypto-fiat liquidity, market segmentation, Bitcoin mining, and legal perspectives.

1.5.1 Capital Controls

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

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

Under tight capital controls, institutional arbitragers would face more challenges when sending money out of the country and might not convert local currencies to USD at a desirable exchange rate. To quantify capital controls, we adopt the dataset compiled by Fernández et al. (2016), in which countries are classified into three categories: Open (least restrictive), Gate, and Wall (most restrictive). Small retail arbitragers face the cross-border money transfer costs if they want to take advantage of price differences. We proxy retail transfer costs with the exchange rate margin charged by the vendor recommended by *Monito.com* and the average margin and transaction fee recorded by the World Bank Remittance Survey.[34]

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

1.5.2 Insufficient Liquidity

But why do we see price deviations even in countries with no exchange rate controls? For example, Sweden imposes little capital control and is labeled as "Open" in Fernández et al. (2016). However, the Swedish Bitcoin price is 5.82% higher than the dollar price, and its returns are only 75% correlated with the dollar returns. The first conjecture is the shortage of liquidity. The total trading volume in Sweden is only 1,214 BTC in 2019, while the trading volume in USD is 16,702,356 BTC.[35] Arbitragers either fail to find enough Bitcoin buyers in Sweden or cannot sell a large number of Bitcoins without bringing the Sweden Krona price down.

We explore whether the trading volume can explain the cross-country variation in return

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

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

asynchronization. Figure A.4 plots the average return asynchronization and log Bitcoin trading volume in 2019. One unit increase in log(volume) predicts 2.83 (t=-6.26) decrease in return asynchronization. The R-squared is 56.6%.

1.5.3 Segmented Trading Markets

Then, we dive into the market structure of cryptocurrency trading. In Sweden, investors typically trade cryptocurrencies through peer-to-peer OTC platforms, such as LocalBitcoins and Bisq.[36] Arbitragers can only sell a tiny number of Bitcoin at a time; for example, the order size per advertisement was limited to 150 - 1,200 SEK on October 8^{th}, 2020; on that date, the Bitcoin price was 98,844.25 SEK. Arbitragers need to post many advertisements and risk that retail buyers might not accept these offers.

Cross-currency arbitrage can be costly even in countries with exchanges to facilitate trading. Korea has six active cryptocurrency exchanges: Huobi Korea, GOPAX, Korbit, Coinone, UPbit, and Bithumb Korea. However, all these exchanges only have active trading in Korean Won—almost no investors buy or sell with US dollars. Arbitragers need to send Bitcoins from a US exchange to a Korean exchange and typically pay various transaction fees: Binance charges 0.04% to withdraw Bitcoin, Coinbase charges 1.49% for fiat currency transactions in the US.[37,38] Sending Bitcoin across exchanges typically would take 30-60 minutes to complete, depending on the blockchain network's congestion. Arbitragers have to bear the risk of price changes during this period.

To quantify cryptocurrency market segmentation, we manually collected trading volume in the last 24 hours from the top 100 crypto-exchanges (ranked by CryptoCompare) on June 10^{th} 2020, and only 75 were active. We compute volume share as the number of Bitcoin traded in one currency divided by total Bitcoin traded on the same exchange. Then, we define the primary trading pair as the currency with the highest volume share. Figure A.5 counts the number of exchanges by the volume share of the primary trading pair. 37 out of the 75 exchanges, de facto, only execute trading in one unique currency. Multi-currency

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

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

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

trading is only active listing platforms or OTC markets without automated market-making; for example, Localbitcoins and Bisq are the two exchanges in the bracket "20-40%" trading volume from the primary trading pair.

Trading volume depletes if we look beyond the primary currency used in the exchange. Figure A.6 summarizes the average volume share of the top 5 active trading pairs. The primary currency accounts for 87.9% of total volume. The number rapidly drops to 8.8% for the second functional currency, 2.2% for the third, 0.8% for the fourth, and 0.3% for the fifth. It is difficult to implement arbitrage across currencies within one exchange.

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

1.5.4 Laws and Regulations

In September 2017, China announced its plan to crack down on cryptocurrency exchanges. Bitcoin trading volume in China plummeted by over 99%. Figure A.8 shows the rise of return asynchronization after the ban became effective in November.[39] Since September 2017, the return asynchronization rose from around 5% to 80% until April 2018. We use the return asynchronization in Hong Kong as a placebo, and it does not respond to the Chinese ban.

Regulations can occur at any stage of the arbitrage. Holding and trading cryptocurrency might be unlawful; regulators can crack down on exchanges; withdrawals of fiat money crypto-exchanges might be subject to capital taxation or anti-money laundering scrutiny. Different countries have different attitudes towards, and legal statuses for cryptocurrency. We manually code cryptocurrency regulations from *Regulation of Cryptocurrency Around the World report* compiled by The Law Library of Congress. Appendix **??** details the laws and

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

regulations of the 31 countries in our sample (USD and EUR excluded). The most crucial dichotomy is whether cryptocurrency trading is legal or not. The United Arab Emirates, Pakistan, and Vietnam explicitly define cryptocurrency as unlawful. Colombia, China, Indonesia, Pakistan, Saudi Arabia, and Thailand implicitly ban or announce policies against cryptocurrencies.[40]

We further look into countries where crypto-trading is legal and investigate their efforts to combat tax evasion and anti-money laundering. Australia, Canada, Switzerland, Czech Republic, Japan, and Korea enact anti-money laundering law specific to cryptocurrencies; Argentina, Brazil, United Kingdom, Israel, Kenya, Mexico, Sweden, and South Africa issue anti-money laundering warnings. Argentina, Australia, Canada, Switzerland, United Kingdom, Israel, Japan, Poland, Romania, Russia, Sweden, and South Africa propose tax laws for cryptocurrency trading.[41]

Table A.11 reports the relationship between return asynchronization and regulations. Among 31 countries, 6 countries do not impose any cryptocurrency regulations. Column (1) implies the 6 unregulated countries experience 13.50% (t = -3.34) higher return asynchronization on average. Within the 25 countries with regulations, Column (2) shows cryptocurrency bans (implicit and explicit pooled) raise return asynchronization by 5.71% (t = 2.12) on average. Unregulated markets and crypto-bans make it difficult to find reliable exchanges to convert fiat currency into and out of cryptocurrencies. Columns (3) and (4) evaluate tax and anti-money laundering laws. Return asynchronization decreases by 7.20% (t = -1.88) and 2.98% (t = -0.72), respectively. Figure A.9 plots return asynchronization by regulatory regimes. Most countries below 10%—Russia, South Africa, Israel, Canada, Japan, Poland, and Pakistan—recognize Bitcoins as a legal investment and collect tax on them.[42]

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

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

[42] India is the only exception where Bitcoin is officially banned. However, domestic investors can still

1.5.5 Concentrated Bitcoin Mining

China is a country where cryptocurrency is legally banned, and strict capital controls have been in place for decades. However, Bitcoin is only 1.31% more expensive than the dollar price, and its average return asychronization is below 10%. Why is that? One possibility is that Bitcoin miners play the role of arbitragers who can sell Bitcoin when the price deviation is too high, and essentially synchronize the Chinese price with the dollar price. China controls roughly 81% of the hashrate of global mining pools.[43] This section documents Bitcoin is cheaper, and its returns are more correlated with dollar returns in countries with Bitcoin production.

We define the production countries as those contributing more than 1% hashrate in Bitcoin mining. Besides China, the Czech Republic accounts for 10%, Iceland, Georgia, and Japan contribute by 2%; and Russia adds mining power by 1%. Four countries with more than 1% hashrate appear in our sample: China, the Czech Republic, Japan, and Russia. The average return asynchronization is 14.4% (t = -2.01) lower in production countries than non-production countries. The average price deviation is 2.7% (t = -1.34) lower in production countries than in other countries.[44]

1.6 Discussion

This section discusses miscellaneous issues. We first document algorithmic trust brought by cryptocurrency and investigate sources of country-level human trust. Then, we validate our model assumption—the positive correlation between local stock market returns and cryptocurrency returns, and further discuss the connection between the Bitcoin price deviations with FX markets. Finally, we explore implications in investment strategies.

purchase Bitcoins with Rupee from many vendors. See https://www.buybitcoinworldwide.com/india/.

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

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

1.6.1 Algorithmic Trust

The foremost question is why investors turn to Bitcoin when they experience less trust? One of the most important feature of cryptocurrencies is the adoption of blockchain technology which replaces human trust in centralized authorities with algorithmic trust. Blockchain—a distributed, decentralized, public ledger—is a "trust machine" that uses an algorithm to verify and process transactions. No trusted authority is needed for people to collaborate, as the algorithm is governed by democracy and will not exploit any agent on the blockchain.[45] Blockchain makes sure that issuers cannot manipulate tokens once the rule enters the system. For example, the total quantity of Bitcoin is set to 21 million. There will not be any further token offerings or buybacks. Issuers cannot benefit from any asymmetric information nor can they potentially exploit investors.

Investors can directly control their cryptocurrency without any third-party or contracting; this security level is the same as gold bullion storage.[46] The private key, a variable in cryptography used to encrypt and decrypt code, fully defines cryptocurrency ownership. Investors' property rights are secured as long as holders can safely keep their private keys. Private keys can be held in digital wallets, Excel files, and can even be written on paper.[47] Moreover, blockchains can provide better security for transactions. Innovators endeavor to create decentralized marketplaces so that Bitcoin holders can trade without delegating their Bitcoins or fiat money to any exchange.[48] At that stage, users can store, spend, and trade crypto-assets without any intervention by third parties.

1.6.2 Economic Foundations of Distrust

Where does trust come from? We analyze the World Value Survey (WVS) to understand why people from some countries trust more than those from other countries. WVS enables us to construct cross-country measures of confidence in institutions and perceived corruption

[45] Appendix **??** discusses how PoW and PoS protocols validate transactions.

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

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

[48] Appendix **??** discusses common approaches for crypto-trading.

in various organizations.[49] For each specific question about a respondent's confidence level in banks, major companies, government, politics, and civil service, WVS reports the percentage of respondents in each of the four categories of confidence level. We assign weight 2 to "A great deal of confidence," 1 to "Quite a lot confidence," -1 to "Not very much confidence," -2 to "None at all," and 0 to "Don't know" or "No answer." We calculate the confidence score as the weighted average of the respondents in each category. Similarly, for each question about perceived corruption in business, civil service, local and state government, we assign weight 2 to "None of them", 1 to "Few of them", -1 to "Most of them", -2 to "All of them", and 0 to "Don't know" or "No answer". The corruption control score is the weighted average of the respondents in each category. The scale of the score is $[-200, 200]$.

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

People who distrust more also believe that corruption is more common. Figure A.11 and Table A.13 report the relationship between trust and the perceived control of corruption in business, civil service, local and state government. Trust corresponds to less perceived corruption, with a slope of 65.17 ($t = 2.15$), 85.10 ($t = 2.18$), 100.9 ($t = 2.25$), 69.73 ($t = 1.92$), respectively.

As Falk et al. (2018) confirms trust measure in GPS is consistent with the WVS, we also validate the correlation between GPS trust and WVS trust in our country sample. WVS has questions regarding general trust in most people, trust people you know personally, trust people you first meet, and trust your neighbor. As before, we assign weight "2" to "Trust completely", "1" to "Trust somewhat", "-1" to "Do not trust very much", "-2" to "Do not trust at all", and "0" to "Don't know" or "No answer". We define the country-level WVS trust score as the weighted average of the respondents in each category. Table A.14 shows that one unit increase in the trust measure in GPS corresponds to 20.92 ($t = 2.01$), 67.13

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

(t = 1.96), 60.38 (t = 2.31), 46.24 (t= 1.51), respectively. The R-Squared of the above regressions are 13.43%, 15.47%, 20.31%, 9.78%, respectively. These results further validate that the two sets of trust measures are consistent.

1.6.3 Assumption Validation

The foundational assumption is that cryptocurrencies are substitutes for domestic investments. With the CRRA utility, $\rho > 0$ implies the substitution across asset classes—investors would allocate more to cryptocurrency when domestic investments become less appealing or riskier.[50]

We validate stocks and cryptocurrencies co-movement, which is $\rho > 0$.[51] In Table A.15, we regress the log BTC/ETH returns on the log value-weighted stock returns in Columns (1) and (2). A 1% increase in log stock return predicts a 0.24% BTC return and 0.49% ETH return. The raw correlations are 5.45% and 5.56%. We further aggregate stock market returns into a weekly time series with all 31 countries equally weighted. Columns (3) and (4) report the time-series regressions: A 1% change stock return translates into 1.39% Bitcoin return, and 2.92% ETH return. The time-series correlation soars to 13.18% for BTC and 13.39% for ETH.

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

1.6.4 Exchange Rates and CIP Deviations

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

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

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

cients of uni-variate regressions of price deviation on lead and lagged exchange rate returns. We find that one-week lagged and simultaneously currency appreciation contribute to the increase in price deviation increase: one bps increase in exchange rate translates into 0.2 bps increase in price deviation. The response shrinks to 0.1 bps with two-week lagged exchange rate returns, and almost zero with more lags. For any shock in exchange rate, about 20% passes into price deviation simultaneously, and takes about two to three weeks to fade away. The relationship itself illustrates the limited arbitrage in cryptocurrency trading.

Do exchange rate impacts contaminate our empirical identifications? The short answer is no. We add currency exchange rate returns and one-week lagged returns to the main specifications in Table A.16. All coefficients basically stay the same in magnitude and statistical significance : from 2.68 (t=2.71) to 2.69 (t=2.71) for Google Trend data on the word "Crisis," 5.99 (t=4.69) to 6.04 (t=4.70) for return asynchronization, 119.4 (t=2.75) to 115.3 (t=2.67) for Bitcoin returns, and 237.8 (t=2.24) to 223.1 (t=2.11) for local stock returns. Consistent with Figure A.13, exchange rate returns do positively predict the price deviations, but orthogonal to factors we identify in Section 1.4.

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

1.6.5 Investment Implications

Given the limits of arbitrage, investors can design trading strategies without moving fiat currency and Bitcoin across the border based on the variables discussed in Section

1.4. Investors can buy Bitcoins when price deviation dips in the local country and sell the same quantity of Bitcoins on the US crypto-exchange, then reverse the process when the local Bitcoin price rises. This section ranks the variables based on their explanatory power in price deviations and argues that factors out-perform in countries with higher levels of distrust.

Based on our analysis, eight factors can explain the variation of price deviations: four Google searches for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for Bitcoin, return asynchronization, past Bitcoin returns, and past local stock market returns.[52] We analyze the R-squared of a set of simple univariate regressions:

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

where $\widehat{Deviation_{c,t}}$ is the demeaned price deviation, and $X_{c,t}$ denotes each of the above eight factors.[53] Table A.18 Column (1) reports the in-sample R-squared of the above regressions on the eight factors individually, and we rank the factor performance based on the R-Squared:

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

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

Furthermore, we evaluate the relationship between R-squared and trust for each factor. Table A.18 Columns (2)-(4) show that factors generally out-perform in medium-trust and low-trust countries compared to high-trust countries.[54] On average, each factor only explains

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

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

[54] For example, Google searches for "Crisis" have an explanatory power of 1.35% in low-trust countries,

0.49% variation in high-trust countries, but 2.89% and 1.72% in medium and low-trust countries, respectively.

Then, we conduct a multi-factor analysis to evaluate the aggregate performance. Table A.19 reports multi-factor regressions to access the marginal explanatory power of each factor. In addition to return asynchronization, institutional failures contribute an extra 1.11% to R-squared. Bitcoin return raises another 2.24%. Stock market returns add 0.18% to the explanatory power. In total, eight factors capture a 6.35% variation in price deviations.

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

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

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

Figure A.14 plots the R-Squared against each country's trust level. Across countries, the average explanatory power of the eight factors is around 23.26%.[55] The slope of the fitted line is -13.69% (t = -1.97). The conclusion also holds if we only focus on institutional failures. Figure A.15 plots the explanatory power of the four institutional failure indices in each country versus the trust level. Similarly, the slope of the fitted line is -13.63% (t =

0.66% in medium-trust countries, and 0.04% in high-trust countries.

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

-1.86).[56] These factors are better predictors in countries with lower trust levels.

1.7 Conclusion

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

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

We integrate trust into a portfolio choice model and highlight that distrust drives heterogeneous price response to demand shocks. Empirical results indicate that price deviations rise as perceived institutional failures increases, Bitcoin and stock markets rally, and arbitrage frictions intensify. Consistent with the model prediction, price responses are augmented in countries with lower trust. Distrust does contribute, at least partially, to cryptocurrency demand.

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

2 Redeemable Platform Currency

2.1 Introduction

As technology blurs the lines between finance and tech firms, and as innovation in transaction technologies continues to disrupt markets, many large platforms are issuing, or considering issuing, their own digital credits or tokens. In principle, Tech firms with a large retail customer base have a natural advantage in creating liquidity by ensuring that their tokens/credits can be used for in-platform purchases. Early implementations include some that are focused on in-platform payment convenience (e.g., Uber and Lyft cash), some began as in-platform and have expanded to more general usage (e.g., Alipay and WePay), while some are designed from the start as general-purpose transactions vehicles (e.g., Facebook's Libra coin).[57] On a smaller scale, but collectively significant, many apps and games offer forms of virtual currency.

Of course, the idea of redeemable credits is hardly a concept new to digital apps, games and currencies (albeit ICOs, with issuance of a large initial quantity, are a modern construct). Airline and retail loyalty points have existed for decades; redeemable S&H green stamps were first issued in the late 1800s, and had become so ubiquitous by the 1960s that the company claimed to have issued more stamps than the US postal service.[58] Nevertheless, despite their long history, the theory of redeemable platform currencies (tokens) remains relatively underdeveloped. The issue may be of broader significance in the future development of digital currencies in that a central issue to regulators is whether new kinds of digital assets offer functionality not embedded in traditional financial assets, and therefore potentially merit consideration for differential regulatory treatment.

Here we present a simple, tractable model of redeemable platform tokens that allows one to explore a number of issues related to their design, features, and supply policy. In principle, such tokens might constitute a prototype currency if they are made tradable (as

[57] There have long been experiments on a smaller scale: for example, Tencent introduced Q-coins for consumers to purchase gaming and non-gaming service provided by Tencent (https://en.wikipedia.org/wiki/Tencent_QQ).

[58] See, for example, Lonto (2013) or Pollack (1988).

opposed to non-tradable).[59] However, this does not mean aiming for a prototype currency is necessarily an optimal strategy unless the tokens generate a considerable convenience yield to consumers (compared to bank accounts). We show that maintaining tradability turns out to imply a number of issuance and pricing constraints that can limit a platform's profits from token issuance. In addition, making tokens tradable constrains the ability of a platform to offer richer token price/quantity menus or to incorporate memory features.[60]

To be clear, our stylized framework is partial equilibrium, and takes both the platform's customer base and their outside banking options as given. In the core model, the gains from trade derive from the platform's ability to earn a higher rate of return on its outside investments than can small retail consumers, though we will also discuss convenience yield.[61] We do not consider gains from trade due to pseudonymity, for example, crypto-currencies that can potentially be used for money laundering, tax evasion, and other illegal activities.[62] Nor do we explore the case where platform currencies supplant government fiat money as a unit of account.[63]

Rather, we explore a narrower case where platforms issue redeemable digital tokens that are indexed to fiat currency. Importantly, the tokens we analyze are more analogous to loyalty points or platform cash than to so-called "stable coins," in that they have a fixed dollar value when redeemed on the platform, but cannot be redeemed directly for cash. From the consumer's perspective, such tokens may be attractive because they are either offered at a discount (the primary focus of our analysis), pay interest, provide a money-like convenience

[59] Tradability is hardly a universal feature of digital assets. Amazon does not permit gift cards balance transfer to another user. Others might allow partial tradability, for example, United only allows 15,000 miles per year to be transferred and charges 1.5 cents per mile transferred, plus a $35 service fee. Nakamoto enabled Bitcoin to be tradable, and now people can buy and sell Bitcoins through brokers without limitations.

[60] The advantages of trying to make loyalty stamps and points largely non-tradable have of course, long been understood by practitioners. Indeed, in 1972, in the case Federal Trade Commission versus Sperry and Hutchinson Trading Co., the Supreme court limited the ability of S&H to make their green stamps non-tradable (see Middlebrook and Hughes (2016)).

[61] Prat et al. (2019) study ICO utility token pricing with a cash-in-advance constraint.

[62] Implicitly we are aiming to look beyond the time when regulation sharply circumscribes such uses. Regulators may also be concerned about potential vulnerabilities if and when crypto-currencies become more integral to the global financial system, see Budish (2018), Raskin and Yermack (2018), Raskin et al. (2019).

[63] For examples of the growing recent literature on Bitcoin and the potential for crypto-currencies to compete with fiat money, see Biais et al. (2020), Athey et al. (2016), Sockin and Xiong (2020), as well as Schilling and Uhlig (2019)

yield, or some combination of the three. For platforms, the advantages include being able to directly tap low-interest retail consumers, to reduce transactions costs, and potentially to benefit from an array of indirect advantages such as strengthening consumer loyalty; these advantages alone can in some cases be significant enough to compensate for having to sell the tokens at a discount that our model endogenizes.

In general, in trying to persuade consumers to hold a significant number of tokens (and thereby garner large seigniorage profits), the core dilemma is this: If the only transaction use of the currency is within-platform, then beyond a relatively modest amount, the coins will have to be sold at a discount that is increasing in the number of tokens sold, or alternatively pay a rate of interest that diminishes the platform's surplus as well as exacerbates fragility issues. Importantly, whether or not a token pays explicit interest can affect how it is taxed and regulated with significant international differences across jurisdictions.

To put the problem we study in context, the first part of the paper presents a brief history of the evolution of different generations of redeemable platform assets from Green Stamps to Ethereum. Even within each generation of redeemable platform assets, there are a wide array of bundling and sales techniques. Although our highly stylized model links most closely to tokens/cash on today's large retailer platforms (such as Amazon, Uber, Alibaba), we argue that some of the insights have links both to earlier versions and to potential new generations of redeemable assets.

The second part of the paper presents our simple partial equilibrium model of platform tokens and their liquidity. We begin by using the model to explore simple strategies where all tokens are sold for the same price in an initial one-time auction, examining both the case of non-tradable and tradable ("prototype currency") tokens. A central result is that the non-tradable tokens can be sold at a higher price (for any given quantity) and yield higher profits to the platform. Essentially, tradability forces the issuer to compete with future resale markets and limits the power to charge a high price upfront. Conversely, and of potential significance in designing future regulation, consumers' share of the gains from trade (due to differing discount rates) tends to be higher with traded tokens.

The next part of the paper explores more sophisticated issuance strategies in which platforms use a price menu approach in their initial coin offering, that is, "buy more and save more". The advantage of a price menu is that the platform can potentially exploit all the potential gains from inter-temporal trade. But again, such an approach only can only work if the token is non-tradable. Indeed, for tradable tokens, introducing a price menu adds nothing to the platform's options. Later, when we introduce tokens with memory, the potential advantages of non-tradability become even more apparent. Our analysis of embedded memory is reminiscent of Kocherlakota (1998)'s discussion of money as a crude form of memory. We also note similar issues to the ones we study here potentially apply to a broader range of digital assets, including gift cards, loyalty points, etc., where firms often impose significant restrictions on tradability.

We then turn to the case where in addition to its "ICO" (initial coin offering), the firm commits to make "seasoned coin offerings" (SCO) sufficient to keep the outstanding stock of coins constant, that is replacing tokens that have been redeemed. Such an approach can enhance credibility, since the platform has an incentive to preserve its ongoing revenue stream. We show, however, that the prospect of future token sales again sharply discourages consumers from holding more than a very limited number of tokens, even if the issuer can credibly commit to its issuance policy (supported perhaps by a trigger strategy equilibrium.) Indeed, in this case there is actually no longer any advantage to making the tokens non-tradable.

The remainder of the paper goes on to relax a number of the simplifying assumptions of the core model, incorporating the possibility of runs, introducing non-zero cost to platform input goods, and allowing for a convenience yield. The most significant extension is to the case of heterogeneous agents. Allowing for heterogeneity creates a number of subtle pricing and issuance questions, for example, should platform token pricing be designed to peel off the most active consumers? However, our main results, on tradability versus non-tradability, and on how appetite for token holdings can be extremely sensitive to future issuance policy, appear to generalize.

The final section concludes, including a discussion of potential extensions.

2.2 Different Generations of Redeemable Platform Tokens

Although modern redeemable tokens are linked to rapid advances in payment technologies, the general idea is hardly a new one. Trading stamps such as Sperry and Hutchinson (S&H) Green Stamps were prominent from the 1930s to the 1980s. S&H sold their stamps in negotiated wholesale transactions to retailers, who in turn gave them as loyalty rewards to consumers (essentially proportional to purchases). Consumers would then paste the stamps into books and redeem them for a wide variety of consumer goods either at S&H stores or via its widely distributed catalog (Pollack (1988); Lonto (2013)). Although S&H was the largest vendor, there were numerous other versions worldwide, for example, the United Kingdom's Green Shield stamps.[64] It is difficult to determine the exact scale of trading stamps, but during the peak of trading stamps in the 1960s, S&H alone claimed to have printed tens of millions of catalogs per year. Interestingly, although trading stamps were essentially as anonymous and as fungible as currency, many of the trading stamp companies attempted to prohibit trade to the extent they could, perhaps, in an effort to prevent a liquid market from emerging.

Improvements in data processing helped enable modern customer loyalty programs. Although airline and hotel programs are the most prominent, there are today a plethora of such programs today around the world in different retail industries. Since American Airlines launched the first airline frequent flyer program in 1981, the space has grown exponentially.[65] Because loyalty programs (in their current guise) are tabulated through a centralized system, the issuer has far more scope to sharply limit tradability. Indeed most do, with enforcement over black markets improving over time especially as government identity protocols have hardened. The size and scale of loyalty programs are enormous, and publicly traded companies are required to report points outstanding and the likely cost of these liabilities. The value of outstanding 20 trillion in airline points is the US alone is worth in excess of $200 billion dollars.[66]

[64] One of the two authors of this paper can claim to have collected and redeemed both the US and UK version of green stamps.

[65] See, De Boer and Gudmundsson (2012), who also discuss how the range and types of airline frequent flyer programs have evolved.

[66] See, example "What is a Reward Point Worth?" by Julie Weed, The New York Times, May 20, 2019.

Table 10: Generations of Redeemable Platform Tokens

Generation	Technology	Circulation Mechanism	Leading Examples	Redeemability	Tradability	Size
First Generation: TRADING STAMPS	Physical stamps (anonymous)	Sold wholesale to retailers then pro-rata to consumers	S&H Green stamps (US), Green Shield stamps(UK)	Convertible to awards at trading stamp stores, or by mail, after filling savers' books	Often legally prohibited, but black market	Peaked in the mid-60s when S&H was printed 32 million catalogs and 140 million savers books
Second Generation: LOYALTY POINTS	Centralized Accounting	Bundled with sales, bonus mechanisms for frequent buyers	Airline and hotel loyalty points, also supermarket and drug stores	Convertible for services of issuing company or partners	Typically constrained with limited black markets	American Airline awards 7-8% of yearly revenue miles for points (8.5 billion outstanding in 2018). Stock equals 20% one year's gross revenue
Third Generation: PLATFORM CASH	Centralized Accounting	Often sold at discount. Very convenient for in-platform use	Uber & Lyft cash, Starbucks stored-value cards, Amazon gift cards, Q-Coin, Gash+	Generally redeemable only on platform but still evolving	Generally none or highly constrained	Uber cash sells at 5% discount (rapidly growing), 3.3 billion Amazon gift cards unredeemed in 2019
Fourth Generation: TOKENS [a]	Cryptography, Blockchain, Cybersecurity Technologies	Initial and recurrent coin offerings (evolving), aims to out-platform uses even to the places with little financial arms	Ethereum, Telegram, Libra, Alipay, Wechat Pay	Can be redeemable for platform services, but usually aspires to universal usage	Tradable or tradable with minor restrictions	Ether can be used for smart contract services, Ether valued at over $60 billion

[a] Stable coins are a special case also redeemable for cash.

American Airlines, for example, reports that it foregoes over 7% of annual passenger revenue due to redemption of frequent flyer miles, and the hangover of existing points amounts has averaged over 20% of gross revenues in recent years.[67] In Table 10, we refer to trading stamps as first-generation redeemable platform assets and loyalty points as the second generation.

As Table 10 illustrates, third-generation redeemable assets include Uber and Lyft cash, Amazon gift cards, Starbucks stored-value cards, Q-coins, and Gash+ (game cash issued by Gamania) appear to be a very rapidly growing phase. A critical distinction between third-generation and second-generation programs is that third-generation tokens are most typically sold for cash, and often at a discount (Uber cash currently offers a 5% discount). This feature is in contrast to 2nd generation assets which are mostly given as a reward, linked to purchases with better terms for more frequent users.[68] Importantly, third-generation platform tokens are very different from first and second generation in that they are extremely easy to use, often involving smaller frictions than any other payment mechanism for in-platform purchases. The potential scale of generation-three platform currencies – which are closest in spirit to what we model in this paper, is vastly larger than earlier loyalty programs simply because the technology has been made much more attractive to consumers, and easier to maintain for suppliers.

Finally, Table 10 lists the fourth-generation redeemable platform tokens. A critical difference is that unlike earlier generations, these tokens can, in principle, be transacted on a shared infrastructure and seek usage beyond the issuer's platform. Massive technological innovations attempt to provide credibility for the fourth-generation assets, for example, public ledgers created from a blockchain without the need for a centralized intermediary. A prominent example is Ether, which can be used (indeed, is required) for smart contracts on the Ethereum platform. Stable coins such as Facebook's Libra are a somewhat different animal, in that in principle, they are not only redeemable for platform services but can be redeemed

[67] The 2019 annual 10-K reports Aadvantage balance is $8.615 billion and $3.362 billion redeemed in 2019, while the total operating revenue is $45.8 billion. The size of redemption would be more sizable given the net income and operating income are only $1.686 billion and $3.065 billion, respectively.

[68] Needless to say, the legal issues behind these new payments mechanisms are still being sorted out, see Middlebrook and Hughes (2016) for a discussion of how case law relating to earlier tokens and currencies might impact on today's versions.

for fiat currency, in many countries as proposed. Whether or not the scale of generation-four platform tokens surpasses generation-three assets is unclear, and much depends on the future of regulation. Finally, we note that the lines between generations 3 and 4 are blurred; Amazon, for example, has shown an interest in extending its financial reach outside of its platform through deals with Western Union and others by Amazon cash.[69] Some voluntary adoption might also happen if a digital currency provides sufficient convenience. For example, Q-coin first-issued in 2002, initially designed to facilitate financial transactions within Tencent's platform, ended up being broadly adopted by many online vendors and gaming companies as a payment method before the rise of WeChat Pay and Alipay.

2.3 A Simple Model

In this section, we develop a partial-equilibrium model to capture how consumers value a token that is underpinned by future claims on platform consumption. The aim is to develop a stylized framework that gives some general insights into how platform tokens might be designed and sold in a modern context.

2.3.1 Consumer Demand

We assume that one unit of the (perishable) platform commodity costs one dollar (there is no inflation in the fiat currency), and provides one unit of consumption. In any given period t, the consumer demands one unit of the platform commodity with probability p, and zero units with probability $1 - p$. All infinitely-lived consumers are identical with time discount factor β. The fact that $p < 1$ captures that the consumer may not need platform consumption every period. The normalization of a single period's consumption to 1 captures limits to the consumer's period demand, but can be varied to study platforms that involve large lumpy expenditures; indeed all the main results here will go through.[70]

[69] "Western Union Partners Amazon for Cash Payments," Yahoo Finance, September 19, 2019.

[70] Define Π as the fiat currency price of a platform good. The scale of a platform depends on $p\Pi$. In our analysis, the price of a unit good is normalized to one. But one can envision of a platform with low-frequency consumption (low p) but a high fiat currency price. One can easily show that all results go through with an arbitrary price of Π for the platform good. That is, platform scale is irrelevant, only the consumption probability matters.

Consumers are risk-neutral and have a utility function that is linear in the consumption of the platform commodity given by

$$U_t = \sum_{s=t}^{\infty} \beta^{s-t} \theta_s C_s \tag{2}$$

where θ_s is the dummy of platform consumption shock in period s: $\theta_s = 1$ with probability p, and $\theta_s = 0$ with probability $1 - p$. θ_s is i.i.d.

2.3.2 Valuing the Marginal Claim

In all that follows, a critical issue is how a consumer values a credit that pays for her M^{th} unit of platform consumption, which will occur at some future date $N \geq M$, depending on the exact timing of the consumer's needs for the platform good. The probability that the consumer will use the M^{th} token in period N is given by

$$X_{N,M} = \binom{N-1}{M-1} p^M (1-p)^{N-M} \tag{3}$$

where $\binom{N-1}{M-1}$ is the binomial coefficient $\frac{(N-1)!}{(N-M)!(M-1)!}$. Given consumers' linear utility function (1), expression (2) governs the value of the marginal claim which is a central input to how much a consumer is willing to pay for tokens.

2.3.3 Platform Currency and Issuance

We now introduce the possibility that platform can issue a "currency" in the form of non-interest-bearing tokens that can be converted to one unit of the platform commodity in any given period. Of course, given the assumed utility function, the consumer will never need more than one token in any given period. Importantly, the consumer is not required to use the platform token and can always pay one dollar of fiat currency (that is, one dollar). As with the consumer, the platform is risk-neutral. To be clear, whereas the platform guarantees the purchasing power of its tokens on its platform, it does not offer to redeem for face value in fiat currency.

The platform discounts the future at $\beta^* < \beta$, to capture that as a large platform, it has better outside investment opportunities than do small consumers.[71] This wedge is the sole source of gains from inter-temporal trade to justify token issuance in our baseline model. It immediately follows that in an efficient equilibrium, with no other liquidity, capital constraints or credibility issues, the consumers would purchase the entire present value of future platform consumption in the initial period, with the allocation of the welfare surplus from trade depending on the relative bargaining power of the two parties, for example depending on consumers' outside options. As noted in the introduction, there may be many other reasons for gains from token issuance, but for the moment, we will focus exclusively on the discount wedge.

One critical issue is the extent to which the platform currency yields a flow of convenience services for transactions inside the platform, and potentially for trade outside, an assumption that is widely used to rationalize demand for currency that pays below the short-term market rate of interest.[72] For now, we assume the convenience yield is zero in all transactions, that the token is only used for platform purchases, and that it does not effectively compete with fiat currency for trade outside the platform. We return to the convenience yield issue later, which is clearly absolutely central to generation 4 platform tokens (from Table 10).

2.3.4 Assumptions

Before proceeding to study token offerings, we initially make a number of assumptions to simplify the analysis, and later discuss what happens when we relax them.

1. Token issuance does not affect consumer demand for platform consumption. This abstracts from a number of possible benefits, for example, if currency issuance increases consumer time spent on the platform.

[71] As Demirgüç-Kunt and Huizinga (2000) show, using bank data across 80 countries, the net interest margin banks are able to earn (the difference between their deposit and lending rates) depend on an enormous range of factors, including both explicit and implicit taxation, leverage market concentration, deposit insurance regulation, macroeconomic conditions and many other factors. Regulation can be expected to play a similarly large role in shaping the net interest margin for tech companies.

[72] Digital currencies clearly can yield substantial convenience: consumers do not need to enter a security code and wait for verification when they pay with Amazon credit. Alipay's convenience service makes Hangzhou a "cash-free" city, where 80% of people make payments with their smartphones, rather than cash or credit card.

2. Zero production cost. This assumption not only abstracts from the cost of producing platform intermediation services, but also from the cost the platform pays in purchasing commodities to sell to consumers.

3. No platform failure or bankruptcy (otherwise a default premium is built into the token). Relatedly, if the platform issues tokens, these are assumed senior to any other debt the platform may issue.

4. The platform can make credible commitments to its future token issuance policy and to redeemability.

5. Any token issued by the platform is effectively a "stable coin" whose platform-use value is fixed in terms of fiat money, and we assume no inflation.

6. Platform tokens are tradable among consumers only if the platform allows it.

These assumptions can be modified to get more general results. In particular, we later allow for a convenience yield, a proportional cost of goods (relax assumption 2), and especially importantly, relax the assumption that the platform can make credible commitments (assumption 4). Other extensions are possible.

2.4 Introduction of Platform Currency through ICOs and SCOs

We now proceed to study the pricing and issuance strategies for a platform that introduces tokens either through a once and for all "initial coin offering" (ICO)[73] or through a combination of an ICO and ongoing "seasoned coin offerings" (SCO). Note that if the platform did not engage in any financial offerings, its value (per consumer) would simply be the expected present value of sales:

$$\frac{\beta^*}{1-\beta^*}p \tag{4}$$

The first-best is that consumers transfer their entire willingness to pay to the platform in the first period. It is achievable by issuing a life-long membership which enables pay once and enjoy the free service for all time. The first-best discounted revenue:

[73] A more precise term would be "initial token offering", however, we follow industry convention.

$$\frac{\beta}{1-\beta}p \tag{5}$$

The present value of revenue after token issuance is bounded by $[\frac{\beta^*}{1-\beta^*}p, \frac{\beta}{1-\beta}p]$. We consider a range of issuance policies and compare policies from the standpoint of the issuer.

2.4.1 Non-tradable Initial Coin Offering

We first consider the case where the tokens issued by the platform are not tradable, and in which the platform announces a fixed (per capita) quantity of tokens that it is going to sell, M. Importantly, in order to sell the full quantity of tokens the platform has put up for sale, all the tokens must be priced at the value of marginal token M, which is the last to be spent. Making use of equation (2), we can solve for the token price in the non-traded case $P_{I,N}$[74]

$$P_{I,N} = \sum_{N \geq M} \beta^N X_{N,M} = \sum_{N \geq M} \beta^N \binom{N-1}{M-1} p^M (1-p)^{N-M} = [\frac{\beta p}{1-\beta(1-p)}]^M \tag{6}$$

One may view $\frac{\beta p}{1-\beta(1-p)}$ as the effective discount rate when the platform aims to issue an extra token. To sell an additional token, all tokens sold must depreciate $\frac{\beta p}{1-\beta(1-p)}$ which yields higher surplus for consumers. Note that we have assumed platform sets the issuance

[74]The last equation uses a combinatorial identity where $x = \beta(1-p)$

$$\sum_{k \geq 0} \binom{M-1+k}{k} x^k = (\frac{1}{1-x})^M$$

An alternative and perhaps more intuitive approach to derive eq.(5) is through induction. Note that with one token, the present value to the consumer is $V(1) = \beta p(1 + \beta(1-p) + \beta^2(1-p)p + ...) = \frac{\beta p}{1-\beta(1-p)}$. Then, we can solve $V(M)$ with an iterative iterative process. In a period when X^{th} token spent, the expected value of $(X+1)^{th}$ token is always $\frac{\beta p}{1-\beta(1-p)}$ where the value of X^{th} token is one. Then, we have

$$V(X+1) = \frac{\beta p}{1-\beta(1-p)} V(X)$$

Thus, the token price of M-token issuance is $V(M) = (\frac{\beta p}{1-\beta(1-p)})^M$.

quantity M, but here it could equivalently set the token price P.[75]

2.4.2 Optimal issuance

To calculate optimal issuance, it is necessary to take into account both the gross profit the platform gets from the ICO and the present value of foregone fiat money sales. As an intermediate step, and to help intuition, it is useful to first calculate the level of currency issuance that would maximize revenue ignoring foregone sales, in which case the platform maximizes $P_{I,N}M$, so that the first-order condition is given by.

$$\left[\frac{\beta p}{1-\beta(1-p)}\right]^M + \ln\left(\frac{\beta p}{1-\beta(1-p)}\right)\left[\frac{\beta p}{1-\beta(1-p)}\right]^M M = 0$$

which implies that

$$M = \frac{1}{\ln\frac{1-\beta+\beta p}{\beta p}}$$

which depends positively on both β and p. Notice that the platform's discount rate β^* does not enter this formula.

Of course, the full maximization problem for the firm involves taking into account that if a consumer purchases M tokens, then she will use tokens for her first M purchases instead of paying in fiat currency. Thus the platform's complete maximization problem is given by

$$\max_M \{ \underbrace{M\left[\frac{\beta p}{1-\beta(1-p)}\right]^M}_{\text{Token Revenue}} - \underbrace{\sum_{i=1}^{M}\left[\frac{\beta^* p}{1-\beta^*(1-p)}\right]^i}_{\text{Foregone Cash Revenue}} \}$$

Define $R_{I,N}$ as the total revenue for non-tradable token issuance. Then, we can rewrite the firm's profit of token issuance as

$$\underbrace{M\left[\frac{\beta p}{1-\beta(1-p)}\right]^M}_{\text{Revenue from Token Issuance}} + \underbrace{\left(\frac{\beta^* p}{1-\beta^*(1-p)}\right)^M \frac{\beta^* p}{1-\beta^*}}_{\text{Revenue in Fiat Money}} - \underbrace{\frac{\beta^* p}{1-\beta^*}}_{\text{No Token Issuance}} \tag{7}$$

[75]The idea that the value and liquidity of a token depend on an underlying matching probability is reminiscent of Kiyotaki and Wright (1989)'s classic general equilibrium search-theoretic model of commodity money.

where the first two terms are the total revenue from token issuance $R_{I,N}$ and fiat sales after all tokens are used.

$$M\left[\frac{\beta p}{1-\beta(1-p)}\right]^M+\left(\frac{\beta^* p}{1-\beta^*(1-p)}\right)^M\frac{\beta^* p}{1-\beta^*}=R_{I,N}$$

The third term in eq.(6) represents the value of the firm in the absence of currency issuance. M^* is a local optimum if

$$\left[\frac{\beta p}{1-\beta(1-p)}\right]^M\geq(M-1)(\left[\frac{\beta p}{1-\beta(1-p)}\right]^{M-1}-\left[\frac{\beta p}{1-\beta(1-p)}\right]^M)+\left[\frac{\beta^* p}{1-\beta^*(1-p)}\right]^M \tag{8}$$

and

$$\left[\frac{\beta p}{1-\beta(1-p)}\right]^{M+1}<M(\left[\frac{\beta p}{1-\beta(1-p)}\right]^{M}-\left[\frac{\beta p}{1-\beta(1-p)}\right]^{M+1})+\left[\frac{\beta^* p}{1-\beta^*(1-p)}\right]^{M+1} \tag{9}$$

Figures 1 and Figure 2 illustrate inequalities (7) and (8). The gray areas represent the net gain and loss from issuing one less (more) token (assuming the optimal number is 3). The blue bars represent the present value of the of the foregone fiat money revenue from the M^{th} token issued $[\frac{\beta^* p}{1-\beta^*(1-p)}]^M$. The dashed bars at the top represent the token price when M tokens are issued $[\frac{\beta p}{1-\beta(1-p)}]^M$. (Here β appears instead of β^*.) For example, Figure 2 shows how if the platform issues one token above the optimum of 3, it gains additional revenue from the extra token issued, but suffers from the price decline on other tokens, as well as the present value of the foregone fiat revenue on the marginal redemption.

A few observations: First, clearly the optimal issuance level M is less than $\frac{1}{\ln\frac{1-\beta+\beta p}{\beta p}}$, which maximizes the firm's gross revenue from token issuance without taking into account the foregone future sales in fiat money. Second, we show that eq.(7) and eq.(8) are necessary and sufficient conditions for the optimal issuance level. In another words, these two inequalities pin down a unique M as the revenue-maximizing issuance quantity. Third, it is straightforward to show that optimal issuance is monotonic in the key parameters β^* as long

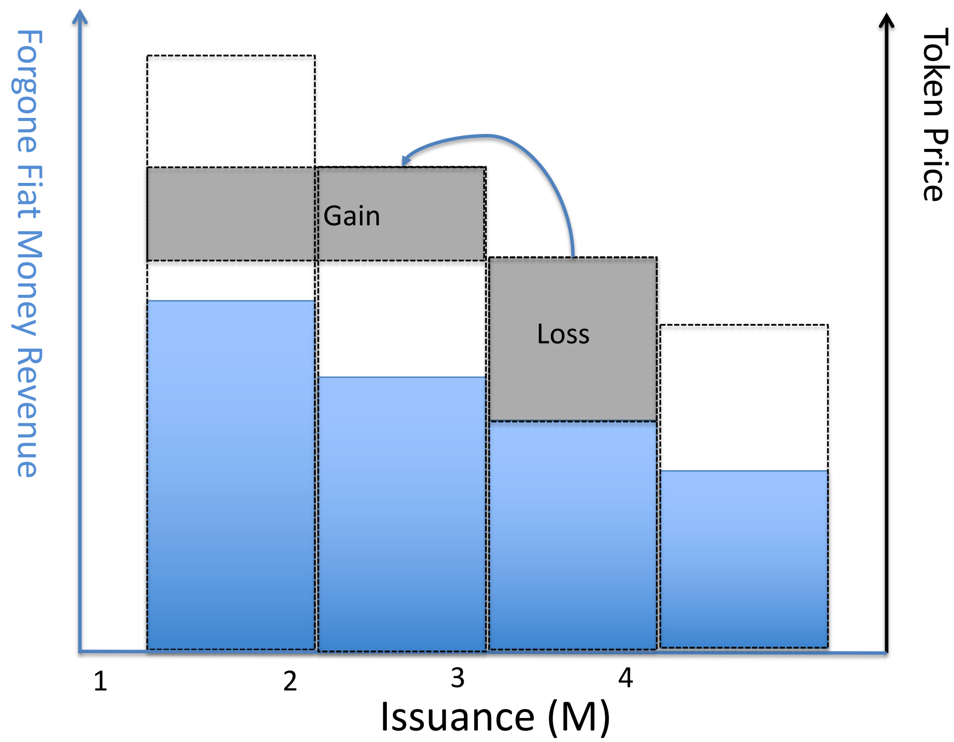


Figure 1 shows the gain and loss by reducing one token (from three to two). The issuer gains from the price increase, but loses from revenue from the marginal token. Given three tokens are optimal in this example, this figure corresponds to optimal issuance constraint eq.(7).

as the optimal issuance level M^* is larger than one. A low-β^* firm values present resources more and prefers to issue more tokens.

Finally observe that with the pure ICO considered here, it does not matter if the platform announces a quantity or a price, since there is complete information, provided the firm is committed to selling all coins at the same price (perhaps because of regulation.) It is this very constraint that leaves consumers some surplus when $M > 1$, and allows them to enjoy some of the gains from token issuance.

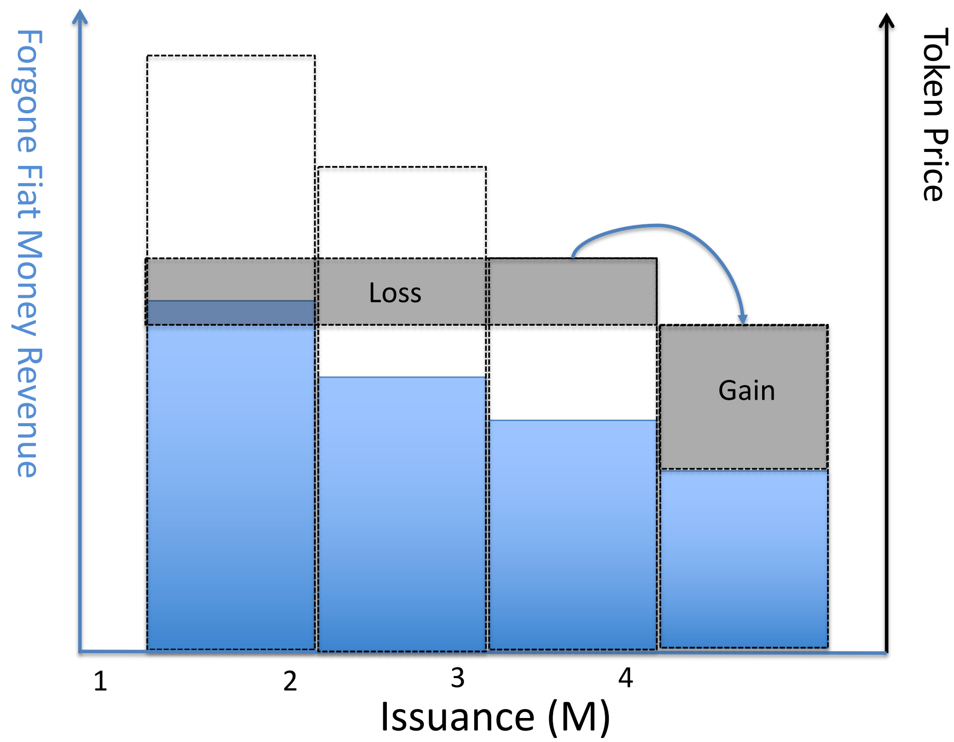


Figure 2 shows the gain and loss from increasing tokens issued from three (optimal) to four. The issuer loses from the price decrease, but gains revenue from the extra token. Given three tokens are optimal, this figure corresponds to optimal issuance constraint, eq.(8).

2.4.3 Tradable ICO

We begin by noting that once all individuals are holding at most one token, the token price is governed by the willingness to pay of individuals who have fully depleted their token supply. If the price is higher than their willingness to pay (WTP), no one wants to buy, and selling pressure pushes the token price down. If the price is lower than the WTP, every consumer without a token wants to buy one and this bids up the price. Thus, the token price is unique when all individuals are holding at most one coin. Let $\widehat{P}$ denote this unique and steady-state price.

$$\widehat{P} = \beta p + \beta(1-p)\widehat{P}$$

The first term on the right-hand side denotes the present value of being able to consume the coin in the next period, and second term denotes the present value of being able to sell it. But this equation can be rearranged to yield

$$\widehat{P} = \frac{\beta p}{1-\beta(1-p)}$$

which is exactly the same as in the non-tradable case. Once all individuals have either zero or one token, there are no longer any gains from inter-consumer trade; a token has the same value to an individual whether she sells it or holds on until she has the first opportunity to use it. Inducing individuals to hold more than one coin, however, requires that they expect the price to appreciate at the rate β^{-1} every period, again assuming as we have so far that the convenience yield is zero.

Now suppose the platform wants to sell M tokens in an ICO, but where tokens are tradable; what is the price? The key observation is that if there are M tokens, it will take $(M-1)/p$ periods for the first $M-1$ coins (per capita) to be depleted. (This is much faster than would be the case without trade.) In period $1+\frac{M-1}{p}$, the price must reach its steady-state value of $\widehat{P}$. The ICO price for M tradable tokens must be given by

$$P_{I,T} = \beta^{\frac{M-1}{p}}\left(\frac{\beta p}{1-\beta(1-p)}\right) \tag{10}$$

To compare the gross revenue from a non-traded ICO of M tokens with a traded ICO of the same size, we first observe that when $M=1$, tradability does not matter since all agents are homogeneous. We then note from equation (5) that to issue one extra non-tradable token, the platform needs to discount token prices by $\frac{\beta p}{1-\beta(1-p)}$ while in the case of tradable tokens, equation (9) implies it would need to discount its price by $\beta^{\frac{1}{p}}$.[76] Thus to compare the price of tradable tokens with that of non-tradable tokens (for any equivalent-size ICO), we need only to compare the two discount factors. Proposition 1 answers this question.

Proposition 1 (Effective Discount Factor Dominance): The effective discount factor

[76] We can immediately derive the ICO revenue maximizing $M = \frac{1}{-log(\beta^{\frac{1}{p}})}$ for the tradable tokens case (ignoring the opportunity cost of lost future fiat money sales). Proposition 1 implies the optimal revenue-maximizing quantity of the tradable ICO is lower than that for non-tradable ICO.

is higher (closer to 1) for non-tradable ICO tokens than for tradable ICO tokens.

$$\beta^{\frac{1}{p}} < \frac{\beta p}{1 - \beta(1-p)} \tag{11}$$

Comments: Proposition 1 states that for any sale of $M > 1$ tokens in an ICO, the price will be higher if the tokens are non-tradable. What is the intuition for this result, given that the expected time to the redemption of the marginal token is greater in the case of non-tradability? The answer has to do with the fact that the consumer's utility function is convex in time of consumption.[77] While commonly known that utility is concave in consumption for any given period, it is less known that the utility is convex in the time of consumption. To illustrate this convexity, consider the following two lotteries in time with the identical expected payoff.

Lottery 1 (Price P_C): One dollar in period $M + 2$.

Lottery 2 (Price P_D): One dollar in period $M + 1$ with 50% probability, and one dollar in Period $M + 3$ with 50% probability.

Lottery 1, sold at a price P_C, delivers payoff one dollar with a "compressed" distribution in time — with 100% certainty in period $M + 2$. Lottery 2, sold at a price P_D, delivers one dollar payoff with a "dispersed" distribution in time — with 50% probability in either period $M + 1$ or $M + 3$. As shown in Figure 3, if one dollar yields the same utility $u(1)$ for any period, then convexity implies that for a given expected cash flow, the more dispersed the distribution in time, the higher it will be priced:

$$P_C = \frac{1}{2}u(1)(\beta^{M+1} + \beta^{M+3}) > u(1)\beta^{M+2} = P_D$$

The initial ICO token price, in both the tradable and non-tradable case, depends on the willingness to pay for the marginal token. Tradability compresses the distribution of the time required to spend the marginal token. In Figure 4, we plot the probability distribution function of the period in which the marginal token is spent with $M = 10$ tokens and

[77] The fact that additive utility functions are convex in time has been previously noted and studied experimentally by DeJarnette et al. (2020)

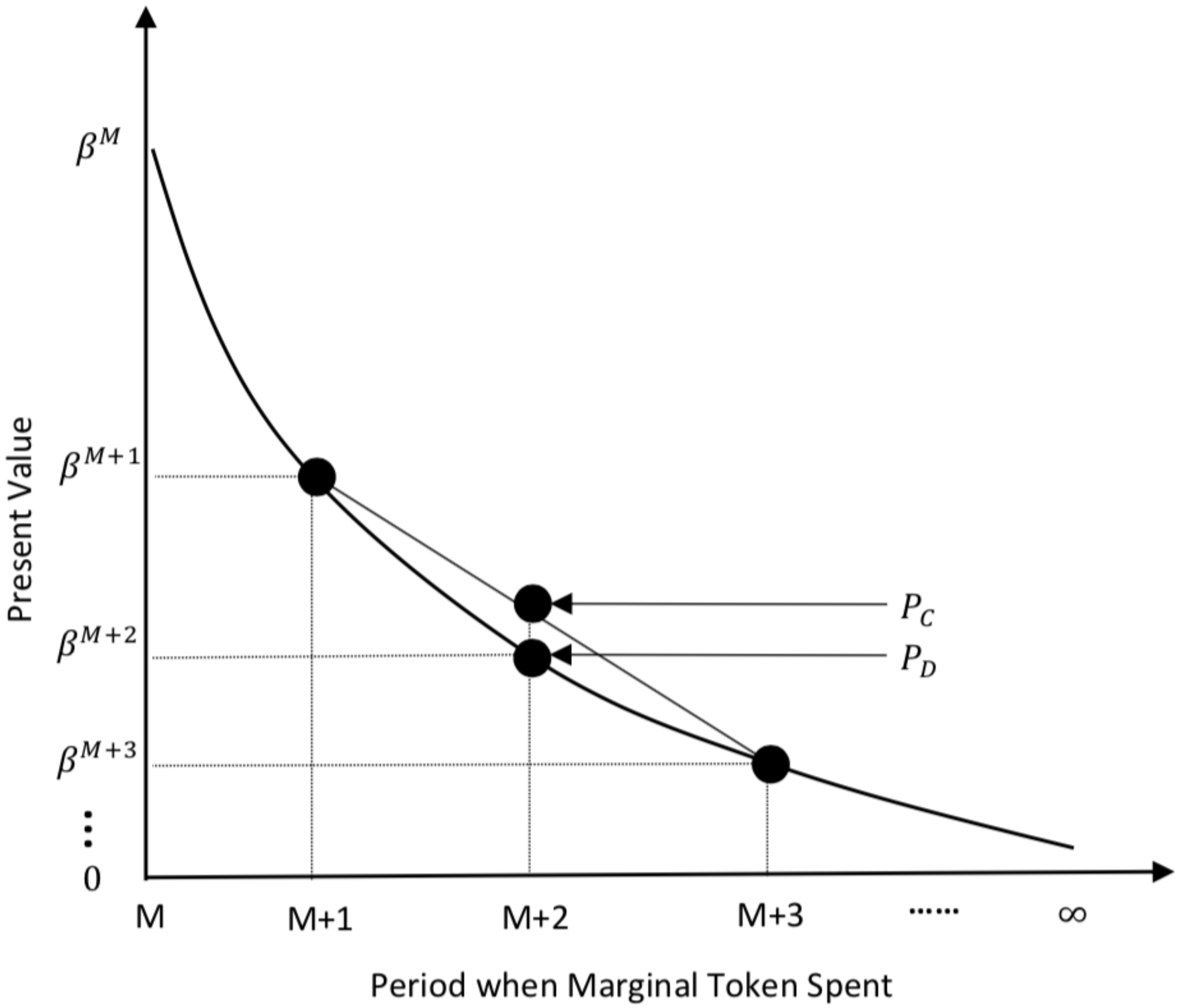


Figure 3 plots the convex $\beta-$discounting function and shows the prices of the following two lotteries: Lottery 1 (price P_C): One dollar in period $M+2$; Lottery 2 (price P_D): One dollar in period $M+1$ with 50% probability, and one dollar in period $M+3$ with 50% probability. Convexity implies $P_C > P_D$.

consumption shock probability $p = 0.5$. All non-tradable tokens might be spent in as few as 10 periods if consumption shocks arrive in every period ex-post, but will typically take a much longer time for most consumers. For tradable tokens, all consumers always use tokens in the first $\frac{M-1}{p} = 19$ periods. As shown in Figure 4, tokens start to deplete in the Period 19 ($\frac{M-1}{p} + 1$) with probability $p = 0.5$. The time distribution of expenditure for tradable tokens is compressed compared to non-tradable tokens. Given the convexity of the utility function in time, tradability thus lowers the token price.

An alternative interpretation is that tradability creates a resale market that pushes the

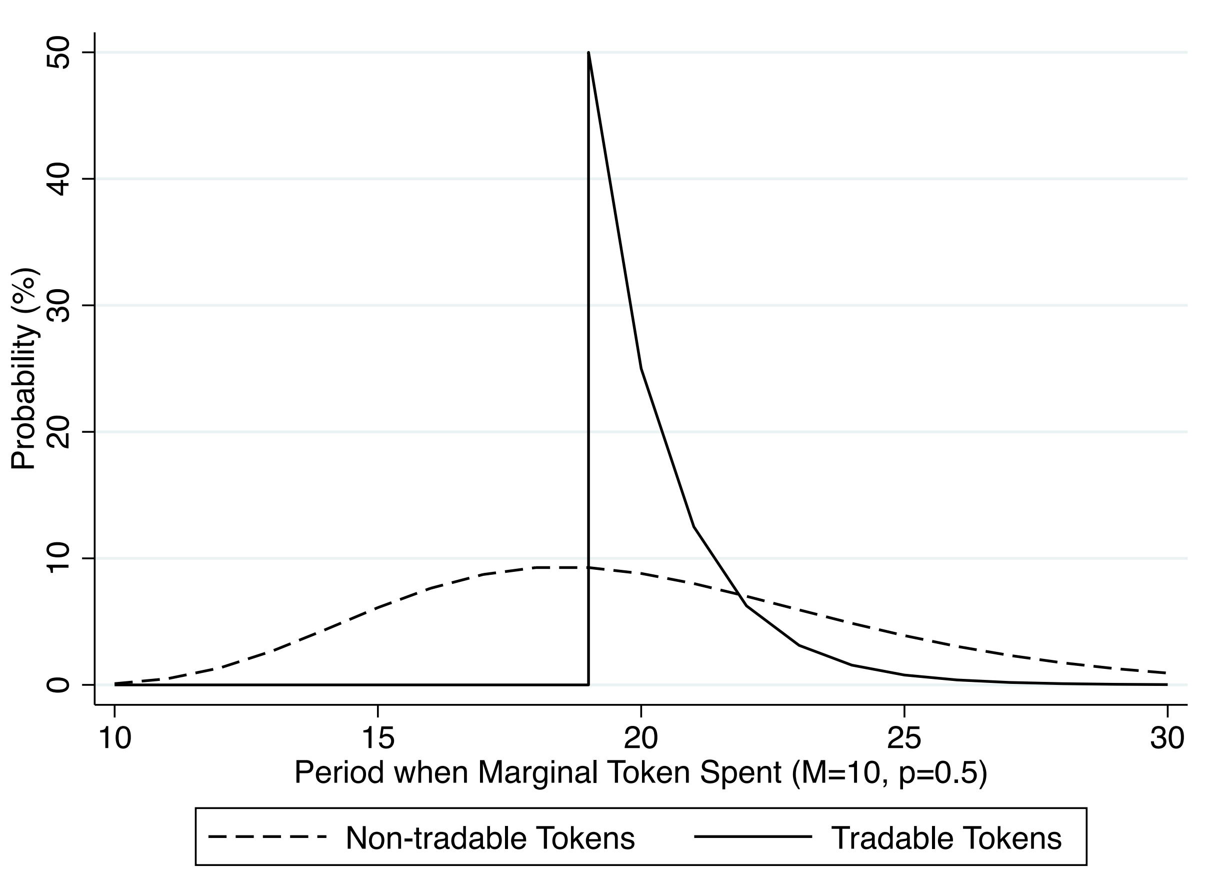


Figure 4 plots the probability the period of the last token spent for tradable and non-tradable ICO respectively. We pick $M = 10$ tokens issued and the probability of consumption is $p = 0.5$. The solid line plots the probability distribution function of tradable tokens. The dashed line plots the probability distribution function of non-tradable tokens.

platform to compete with itself. (This interpretation has a loose analogy to the Coase conjecture albeit here consumers are homogenous.) The resale market introduces competition with the future and reduces the token price. One might ask how a tradable token can sell for less than a non-tradable token when the consumer always has the option of not trading it. The answer is that with tradability, the platform cannot command as high a price precisely because the consumer knows there is always an option of buying on the outside market in the future, and this drives the requirement that the market price of a tradable token must rise faster than the shadow price of a non-tradable token, as we have just proven. As we shall see in later sections where we look at richer pricing strategies and memory functions, the potential advantages of non-tradable tokens run much deeper than just this point.

Of course, the proceeds from the ICO do not capture the entire story, since whenever a consumer tenders a token for a later purchase, the platform has to forego fiat currency revenue that it would have enjoyed absent any token issuance. But, as we next demonstrate in Proposition 2, the present value of future fiat revenue sales is also higher when tokens are non-traded, so a non-traded token ICO is unambiguously more profitable than a traded token ICO.

Recall that $R_{I,N}$ is the total revenue from non-tradable token issuance, given below eq.(6). Define $R_{I,T}$ analogously.

Proposition 2 (Revenue Dominance): Tradability reduces the discounted revenue of the issuer.

$$R_{I,N} > R_{I,T}$$

Proof of Proposition 2

The present value of firm revenue from a one-time tradable token ICO, including both the initial token sales revenue, and revenue from future fiat currency sales is given by

$$\begin{aligned} R_{I,T} =& M \times P_{I,T} + {\beta^*}^{\frac{M-1}{p}} \frac{\beta^* p}{1-\beta^*(1-p)} \left(\frac{\beta^* p}{1-\beta^*} \right) \\ &< M \times P_{I,N} + \left(\frac{\beta^* p}{1-\beta^*(1-p)} \right)^M \left(\frac{\beta^* p}{1-\beta^*} \right) = R_{I,N} \end{aligned} \tag{12}$$

This inequality ${\beta^*}^{\frac{1}{p}} < \frac{\beta^* p}{1-\beta^*(1-p)}$ holds as the β^* version of the condition proved in Proposition 1.(That is, simply substitute β^* for β and the proof follows.) The only case where tradability does not affect the discounted revenue is where $p = 1$ or $\beta = 1$.

Comments: The logic is simple: The issuer starts to earn revenue in fiat money earlier with non-tradable tokens than with tradable tokens.[78] For the first M periods, all agents

[78]With tradable tokens, no consumer would pay fiat money to the platform until period $\frac{M-1}{p}$. If tokens are not tradable, a "lucky" consumer can spend all M tokens before period $\frac{M-1}{p}$ and thereafter pay fiat money for the platform consumption.

under both types of ICOs have at least one token, and p percent of them use it each period. But starting after period M, a rising fraction of agents in the non-tradable ICO have no coins, and thus need to use fiat money for platform consumption. Under a tradable ICO, agents who hit zero coins can buy coins from agents who have two tokens or more; in fact, all agents have at least one coin for the first $\frac{M-1}{p}$ periods. Thus revenue from fiat money is more backward loaded with tradable issuance than non-tradable issuance, and hence has a lower present value.

For only in-platform use, tradable tokens are strictly dominated by non-tradable tokens in both revenues from token issuance and revenues from fiat money. To justify tradability, there must be additional benefits outside our model. Of course, it is true that in our setup, we are neglecting several potential merits of tradability. First, tradability makes the tokens liquid, and potentially would allow the platform to pay a lower return due to a liquidity premium, albeit one that is likely lower than on fiat currency. Second, we have been assuming risk neutrality; if agents are risk-averse in period utility, there would again be gains to tradability. Third, we have eliminated the possibility that the tradable token can be used at other platforms or peer-to-peer transfer. There are many crypto-exchanges that provide services for token trading, for example, Coinbase or Bitpanda. If tradability allows broader use of the token, which might be translated into a higher p in our model, this again could be an advantage of tradability that is outside the scope of our model.

2.4.4 Consumer Surplus

Token issuance yields gains from trade given that the platform's rate of return exceeds that of retail bank consumers. However, the quantity-price tradeoff implies that the issuer is unable to claim the entire surplus, and must share part of surplus from token issuance with consumers. For completeness, and since the issue might be of significance to regulators, here we explicitly derive consumer surplus.

Consumers derive utility $\frac{\beta p}{1-\beta}$ from consumption but can pay for it in either tokens or fiat money. The consumer's spending consists of two parts: token spending today, and the expected expense in fiat money after depletion of tokens. For the non-tradable tokens, we can also write the consumer surplus as the total willingness to pay for the first M tokens minus the cost of purchasing the tokens.

For non-tradable ICO tokens,

$$\begin{aligned} CS_{I,N}(M) &= \underbrace{\frac{\beta p}{1-\beta}}_{\text{Consumption Utility}} - \underbrace{M \times P_{I,N}}_{\text{Token Spending}} - \underbrace{\left(\frac{\beta p}{1-\beta(1-p)}\right)^M \left(\frac{\beta p}{1-\beta}\right)}_{\text{Fiat Money Spending}} \\ &= \underbrace{\sum_{i=1}^{M}\left[\frac{\beta p}{1-\beta(1-p)}\right]^i}_{\text{Consumption Utility from First M Goods}} - \underbrace{M \times P_{I,N}}_{\text{Token Spending}} \end{aligned}$$

For tradable ICO tokens,

$$CS_{I,T}(M) = \frac{\beta p}{1-\beta} - M \times P_{I,T} - \beta^{\frac{M-1}{p}}\left(\frac{\beta p}{1-\beta(1-p)}\right)\left(\frac{\beta p}{1-\beta}\right)$$

Almost parallel to the Proposition 2, we can easily show that tradable tokens are preferred by consumers: $CS_{I,T}(M) > CS_{I,N}(M)$.[79] Consumers benefit from tradability from both lower token price paid today and the later fiat-money spending on expectation in future. In our model, consumers always prefer a free market while the issuer benefits from more restrictions on consumers for a more favorable split of welfare gain. $CS_{I,N}(M)$ and $CS_{I,N}(M)$ fully incorporate the β convexity effect we discussed earlier, implying the price effect dominates for consumers.

2.4.5 Non-tradable ICO with a Price Menu

We now consider the possibility that instead of selling all tokens at the same price, the platform is allowed to offer a menu that relates the total price paid to the number of tokens sold. Consumers are able to get a lower average price, the more tokens they buy. In this case, it is easy to show that the firm can garner all the gains from trade and leave zero consumer surplus.

[79] The only difference is that consumers discount the fiat-money spending with β, rather than β^* on the issuer's side. $\left(\frac{\beta p}{1-\beta(1-p)}\right)^M \left(\frac{\beta p}{1-\beta}\right) > \beta^{\frac{M-1}{p}}\left(\frac{\beta p}{1-\beta(1-p)}\right)\left(\frac{\beta p}{1-\beta}\right)$ holds by Proposition 1.

To derive the its optimal price menu,

$$\sum_{i=1}^{M}\left[\frac{\beta p}{1-\beta(1-p)}\right]^{i}$$

In this case, as $M \to \infty$, the platform gets the maximum possible discounted revenue (first-best) out of consumers

$$lim_{M\to\infty}\sum_{i=1}^{M}\left[\frac{\beta p}{1-\beta(1-p)}\right]^{i}=\frac{\beta p}{1-\beta}$$

Consumers get zero surplus since the platform can design a price menu so that consumers are indifferent along the menu. Thus, the design of price menu pushes up the average token price and therefore total platform revenue corresponding to any given token issuance.[80,81]

$$P_{I,PM}=\frac{\beta p}{1-\beta}[1-(\frac{\beta p}{1-\beta(1-p)})^{M}]\frac{1}{M} \tag{13}$$

It is quite straightforward to prove that a price menu approach adds nothing when the tokens are tradable: if the platform sells at a lower average price to bulk, token buyers, it cannot prevent the arbitragers from making a profit through resale. (Nor can it stop coalitions of consumers from buying in bulk to get a lower average price.).

2.4.6 Credibility of One-Time ICOs

It is important to emphasize that in the ICO case we have considered until now, the platform will be tempted to issue more tokens as the supply dwindles. Obviously, this could devalue the existing base in the case of tradable tokens, but the possibility also turns out to be relevant even in the non-tradable case. As we shall see in the next section, the consumer

[80] If consumers can share information efficiently and ship products at a low cost, one customer can arbitrage along the price menu by aggregating demand from other consumers, buying a large quantity from the issuer at a low price, and shipping products to others. In reality, customers are willing to accept price discrimination if it is costly to arbitrage in the product market or if the purchased service is not transferable at all. For example, users have to link their Uber accounts to their cell phone numbers. Thus the nature of some businesses can make a price menu approach feasible in reality. However, for some durable goods, say an iPhone, the shipment cost is quite small compared with the product value.

[81] $\frac{\beta p}{1-\beta}[1-(\frac{\beta p}{1-\beta(1-p)})^{M}]\frac{1}{M} > (\frac{\beta p}{1-\beta(1-p)})^{M} = P_{I,N}$

may regret having bought so many tokens in the ICO and wish instead she had earned interest on her savings and purchased more tokens later. Put differently, expectations of future issuance affects the shadow price at which the implicit value of tokens will rise. Thus in both cases, traded and non-traded ICOs, expectations of future issuance affects the current value of tokens. Our analysis, therefore, assumes not only that the platform is credibly able to commit to the purchasing power of the tokens when tendered, but also to its issuance strategy.

As a private sector business subject to national laws and courts, a platform may have at its disposal some devices for enhancing credibility not available to a sovereign currency issuer. For example, it can be subordinated to a regulator who ensures that the platform's "white paper" describing its token issuance policy cannot be violated without severe penalties. The ICO tokens can be made senior to other debt and to any tokens issued in the future. Similarly, the platform is legally bound to honor the fiat currency value of its tokens, so the exchange rate is fixed. Obviously, many subtleties and nuances are surrounding all these issues, and the issue of credibility is fundamental.

In the next section, we consider a class of richer issuance strategies, beyond a one-time ICO, that helps illustrate some of these points.

2.4.7 Non-tradable/tradable ICO+SCO (Price Only)

Until now, we have considered one-time token issuance strategies that, over time, lead to a shrinking supply of tokens as consumers redeem them for in-platform purchases. A true prototype currency would not self-extinguish, particularly if the issuer wants to maintain the possibility of eventual use outside the platform. In this section, we introduce the possibility that after the initial ICO, the platform commits to subsequently engaging in routine "SCO" (seasoned coin offerings) sufficient to maintain a constant steady-state supply of tokens. Although we are going to continue to assume that the platform can credibly commit to its issuance strategy, understanding how the expectation of ongoing sales affects the price of the initial ICO is also relevant to understanding how lack of credibility might affect initial issuance and price.

The introduction of SCOs turns out to change the calculus of token issuance quite fundamentally. In particular, we will demonstrate here the strong result that if SCOs are used to maintain a constant supply of tokens, then the maximum number of coins consumers will hold is one per person. This result is the same whether tokens are tradable or not, and in fact the tradable and non-tradable cases become equivalent. Importantly, this result applies only to the kind of "memoryless" tokens we have been considering so far; later we will introduce the possibility that that platform can condition future token sales to individuals on past purchases.

We begin with the case of non-tradable tokens. One new question in this scenario is how to set the price in the SCO. In principle, there are three issuance strategies. (1) A no information policy, in which all consumers are offered the same price in every SCO regardless of their history in purchasing tokens and spending them. (In Section 5, we consider SCO issuance with memory.) (2) A history-dependent policy where the platform can charge a price for SCO tokens that is a function of the consumer's entire history with the platform. (3) A Markov policy where issuance depends only on the consumer's current account information (holdings of tokens) but is not path dependent. Policies (2) and (3) may seem very "un-money like" but actually incorporate the richer possibilities that digital currencies offer, ideas that are seldom considered in contemporary policy discussions say, about how retail central bank digital currencies might replace paper currency.

In this section, we will focus on the "no information" policy that is perhaps most likely to be regulatory-compliant and least likely to run afoul of privacy concerns, though later we will consider strategies with memory. The no information SCO strategy has very stark implications. The basic problem the platform faces is that for any steady state M it tries to sustain, consumers will only be willing to hold excess coins – more tokens that can be spent in one period – if they anticipate that the price will be rising over time at the consumer's implicit interest rate (β^{-1}). But this is only possible in equilibrium if the quantity of tokens is falling over time – which is a contradiction unless the excess coins yield sufficient transactions convenience services, which we are abstracting from throughout most of this paper. Thus, the only steady-state coin holding has every consumer entering each period with exactly one token. At the end of the period, the platform will offer p tokens per person at price

$$P_S = \frac{\beta p}{1 - \beta(1-p)} \tag{14}$$

which of course corresponds to the ICO price at $M = 1$. In a sense, we might refer to this equilibrium as a "token-in-advance" model, since the consumer is always using tokens for platform purchases. The same result holds with tradable tokens.

Proposition 3 (Token-in-advance Theorem): In any equilibrium with a constant supply M of tokens, and with memoryless issuance strategy, $M = 1$ regardless of tradability.

Proof of Proposition 3:

First, the token price needs to be constant in every period. If the token price is expected to appreciate indefinitely at the interest rate, one token will eventually worth more than the market value of the platform. However, the token price cannot exceed one because the value of underlying consumption is bounded (at one by assumption). With a constant token supply, the price must also be constant. Therefore consumers cannot get capital gains to substitute for explicit interest payments, and the equilibrium token supply (per capita) cannot exceed one in both tradable and non-tradable issuance.[82]

Define R_S as the total revenue of the ICO + SCO ("token-in-advance"):

$$R_S = \underbrace{\frac{\beta p}{1-\beta(1-p)}}_{\text{Token revenue today}} + \underbrace{\frac{\beta^* p}{1-\beta^*}\frac{\beta p}{1-\beta(1-p)}}_{\text{Token revenue in future}}$$

The issuer nevertheless gains a higher discounted revenue from issuing one token than with no tokens.

$$R_S - \frac{\beta^* p}{1-\beta^*(1-p)} = \frac{(\beta-\beta^*)p}{(1-\beta+\beta p)(1-\beta^*)} > 0$$

[82] No consumer would buy a second token since any consumer would prefer to invest in the risk-free asset and wait to buy a new token from the market or from the issuer after the next consumption shock arrives.

Comments: Despite being able to earn ongoing revenues, the platform can only sell one token in the first period, and only $p < 1$ tokens per period thereafter. Of course, from the point of view of credibility, this ICO+SCO equilibrium might be easier to implement than the ICO. Also, the "token in advance" model might be more viable in an environment where consumers face liquidity constraints.

2.4.8 Comparison of ICO+SCO with Non-tradable ICO

From a revenue perspective, an ICO+SCO allows the issuer to secure ongoing token revenue from all future SCOs, rather than only from the one-time initial ICO. Also important is the fact that by releasing tokens more slowly, the platform will be able to get a higher (un-discounted) average price, that is, garners a larger share of the gains from trade. The disadvantage, of course, will be the expectations of future SCO issuance limits how much the platform can front-load revenue into the initial ICO. A natural question is whether a non-tradable ICO issuance mechanism can beat the simple ICO+SCO with the "token-in-advance" constraint. This involves comparing the discounted revenue of the non-tradable ICO:

$$R_{I,N} = \underbrace{M(\frac{\beta p}{1-\beta(1-p)})^M}_{\text{Revenue today}} + \underbrace{\frac{\beta^* p}{1-\beta^*}(\frac{\beta^* p}{1-\beta^*(1-p)})^M}_{\text{Revenue in future}}$$

Proposition 4 (ICO versus ICO+SCO Dominance): Under optimal issuance, the non-tradable ICO dominates ICO+SCO if β^* is sufficiently low ($\beta^* \to 0$). When the consumption probability p is low ($p \to 0$) or β^* is high ($\beta^* \to \beta$), an ICO+SCO dominates the non-tradable ICO.

Comments: The tradeoff between ICO and ICO+SCO essentially depends on the size of gains from ICO token issuance. For any parameters, it is easy to compare numerically with the closed-form expression of $R_{I,N}$ and R_S. Proposition 4 studies the dominance in three extreme cases: When p is too small or the issuer's discount factor β^* is close to the consumer's discount factor β, the issuer may prefer to do the ICO+SCO issuance mechanism because the issuer can benefit from "token-in-advance" in every future period while the issuer cannot benefit a lot from the large-quantity issuance in the ICO. For example, one can show that the ICO+SCO strictly dominates the non-tradable ICO in the parameter space where the optimal issuance quantity is 2 (two) under the non-tradable issuance.[83] The non-tradable ICO will dominate the ICO+SCO when the issuer is impatient enough (β^* is small). The benefit of the front-loading cash flow can be sufficiently large to offset the loss of future SCO revenue.

Certainly, the ICO + SCO with a constant steady supply of tokens and a constant steady-state price is much simpler than the optimal one-time ICO. It is also straightforward to show that for reasonable parameters, it can be supported as a trigger strategy equilibrium if we relax the no commitment assumption. Indeed, if the platform lacks credibility, the equilibrium can devolve to the ICO + SCO case ("token-in-advance"). However, absent credibility issues and when p and β are both close to one, the one-time non-tradable token ICO is much more profitable.

2.5 Assumptions Revisited

2.5.1 Runs and Interest Payments

As the model is constructed, the platform tokens are not subject to runs because agents tender their tokens if and only if a consumption shock hits, and the good is assumed non-storable. Of course, in reality, the offerings of platforms such as Alibaba and Amazon cover a wide range of durable goods, which opens the possibility of having a panic with say, consumers using their tokens to buy durables they do not yet need, despite storage costs. The platform can deal with runs in standard fashion, for example, by reserving the

[83] We compute the revenue of a non-tradable ICO minus the revenue of an ICO+SCO when the optimal token issuance is 2 under the non-tradable ICO. The revenue gap is strictly negative when $\beta^* < \beta$

Denote $a = \frac{\beta p}{1-\beta(1-p)}$ and $a^* = \frac{\beta^* p}{1-\beta^*(1-p)}$. Conditional on $M^* = 2$, we can show that $R_{I,N} < R_S$:

$$R_{I,N} - R_S = 2a^2 + \frac{a^*}{1-a^*}a^{*2} - a - \frac{a^*}{1-a^*}a = a^{*2} + \frac{a^*}{1-a^*}(a^{*2} - a) = \frac{a^*}{1-a^*}(a^* - a) < 0$$

right to suspend sales temporarily, but the point is that even commodity-backed platform currencies are not immune to runs absent a fully-credible outside guarantee.[84] Of course, in principle, the proceeds from token sales can be deposited in low return, but highly liquid, government securities. The platform could have a guaranteed refund in fiat currency if it were to temporarily stock out of goods in any given period; then, however, it would enjoy much smaller profits from token issuance.[85]

Some crypto-currencies have indeed adopted a business model of setting a fixed exchange rate and claiming to hold all assets in treasuries, with the idea of making a profit by selling at par, paying zero interest, and then making a profit from the interest-bearing government assets. This approach, of course, has its fragilities. First and foremost, once international government regulation requires these assets to be easily traceable by governments and fully compliant with tax evasion and anti-money laundering laws, it is not at all clear that consumers will recognize any "convenience yield". Second, even the most efficient crypto-currencies require considerable business costs to run. Last be not least, they are ultimately subject to the same kinds of fragilities as fixed exchange rate currencies and currency boards, where even slight temporary illiquidities or fiscal weakness can lead to an immediate attack. (See, for example, Obstfeld and Rogoff (1995).)[86]

Another approach for the platform would be simply to create an outside bank to handle its tokens, aiming to combine or leverage its token issuance business with a standard bank-like lending business. This approach would thereby create a chaebol or keiretsu-like structure which might allow the platform to use data across businesses to create synergies. The competition between tech companies and banks is a critical area but beyond the scope of this paper. Our narrow point here, though, is that the ability of chaebol and keiretsu to back tokens with platform goods does not necessarily constitute a significant advantage in itself.

Finally, we note that in principle, platform tokens can pay interest "in-kind" (in tokens) rather than in fiat currency. In particular, suppose tokens pay interest equal to $\frac{1-\beta}{\beta}$ on an

[84] The classic reference on pure multiple equilibrium bank runs is Diamond and Dybvig (1983).

[85] The platform can also adopt a policy of suspending service in a stockout to discourage runs.

[86] For a discussion of the fragility of crypto-currencies, see Rogoff (2017)

ICO of $\frac{\beta p}{1-\beta}$ tokens, which could be tradable. This policy is sustainable since it involves paying out p tokens per period, exactly enough to replace tendered coins, assuming no runs. In a sense, this is a different implementation of lifetime memberships. Another important interpretation of the interest-bearing token we have just detailed is as a "security token" where effectively the consumer owns a share of the platform, with payments in services. We leave "security tokens" for future research.

Why then, shouldn't the platform always make its tokens interest-bearing, or perhaps security tokens per the above example? There are at least a couple of reasons. First, and perhaps of the greatest concern in practice, is that the taxation and regulation of interest-bearing tokens may be very different than non-interest bearing tokens, bringing the platform issuance under banking and/or securities market regulation, with different results in different jurisdictions. Current generations of tokens from Uber cash to Libra go through many gyrations to avoid being classified as securities, with non-payment of interest being a central condition in the United States and most major jurisdictions.

Second, in a more general model with uncertainty, the required interest rate will fluctuate. And if the token market is relatively illiquid, it may be difficult to calibrate the interest rate required to fulfill the platform's initial pledge to pay market interest. In general, paying interest generates a different class of credibility issues, which are some cases may be more difficult to navigate.

2.5.2 Non-zero Cost of Input Goods

Assumption 2 posits zero cost of goods so that the entire revenue converts into platform profit. We relax this assumption by allowing X proportion of platform sales to be attributable to the input cost of goods. In this case, potential token demand is equal to gross sales by the platform each period, and not just net revenues.

The logic is straightforward: Token issuance adds financial income at the scale of gross revenue, which can be much larger than the size of profit from net platform revenue. For example, if an online retailer platform has a profit margin of 5%; the platform can issue tokens with denomination 20 dollars for each one-dollar profit. If the platform can create an interest return wedge of 3%, the value-added from token issuance will be 0.6 dollars, which account for 60% increase in the platform profitability.

The pricing equations and issuance policy results remain the same as before when we relax the zero cost of goods assumption, except that token prices are proportional to gross sales, not net platform profit. The token prices only depend on the consumption probability, the sale price of the commodity, and the effective discount rate. Thus the breakdown in cost and profit does not affect the willingness to pay (WTP) for tokens. Thus, the value-added of token issuance is wholly determined by the revenue and not affected by the cost of goods.

The only change to the analysis from introducing non-zero input costs is to leverage up the present value of the platform's profits from token sales. We consider the maximum leverage effect from the benchmark platform value without token issuance to the first-best platform value.

The present value of platform without digital currency

$$\frac{\beta^*}{1-\beta^*}pX$$

Under the first-best, the present value of platform profit is

$$\frac{\beta}{1-\beta}p - \frac{\beta^*}{1-\beta^*}p(1-X)$$

The value to the platform of being able to leverage token issuance can be as high as

$$Leverage(X) = 1 + \frac{\beta-\beta^*}{\beta^*(1-\beta)}\frac{1}{X}$$

where $Leverage(X)$ is monotonically decreasing in X and β^* (increasing in the platform investment return), and orthogonal to the consumption probability p. A low X in practice makes the token issuance to be spectacularly attractive for the online platforms with voluminous transactions but low profitability. Thus, in principle, token issuance has great potential when internet companies become financial service providers. Of course, as leverage increases, credibility problems become exacerbated and the platform becomes more vulnerable to runs per our earlier discussion.

2.5.3 Convenience Yield

One important potential merit of platform tokens is in providing a convenience yield for the token holders.[87] In the money-in-the-utility model (Sidrauski (1967)), utility is increasing and strictly concave in real money balances. In our model, a convenience yield would directly affect the token price by changing the effective discount rate. A larger convenience yield for consumers clearly benefits the platform which can then discount its tokens by less.

Convenience yield might be able to justify the issuance of tradable tokens if tradability brings greater convenience for transactions. For example, suppose tokens can be used as a digital unit to transfer money among consumers. In this case,

$$\beta(M, N) < \beta(M, T)$$

When tokens are more convenient to use, token holders are effectively more patient when holding tokens and willing to pay more fiat money in exchange for them. Where the government allows it, and where a single firm has dominant share across a large range of the economy, it is possible in principle that a platform currency could yield a significant enough convenience yield to compete with a government currency. For example, Alipay's success in China, particularly in Hangzhou, brings together payments for online shopping, restaurants, investment funds - even public transportation - into one unified digital payment system. This convenience has persuaded the younger generation to start keeping a large proportion of their savings in their Alipay's accounts. Tradable digital currency has great potential to be much more convenient than cash if the infrastructure is appropriately built.

Analytically, a convenience yield is quite straightforward to incorporate into our model if it is linear in token holdings (it simply modifies the consumer's discount factor β). A more general treatment, allowing for decreasing returns, would be more challenging. In any event, our read of the centuries-old history of money is that the government may initially allow

[87] For example, payment with Amazon credit can be settled immediately, rather than going through credit card verification.

or even foster private innovation in transaction technology, but eventually the government regulates and appropriates.[88]

2.6 Money Memory

Up until now, we have shown that for a given level of token sales M in a one-time ICO, a platform will earn a larger profit from a non-tradable token than from a tradable token, and a larger profit still with a "buy more, save more" price-menu approach. If instead, the platform attempts to maintain a constant supply of outstanding coins with the ICO + SCO, the tradable and non-tradable cases turn out to be equivalent; whether or not the ICO + SCO can beat the one-time non-tradable ICO depends on β and p.

An important potential feature of a platform-backed currency – and in principle for any digital asset – is memory.[89] A platform can fully observe a consumer's account information, the full history of the account, and even the entire transaction history for each token. Making use of this information, a platform can design a mechanism for the SCO that induces consumers to hold $M > 1$ despite knowing that there will be future SCOs to replenish their stock.

We show that profitability of the ICO + SCO can be considerably enhanced if the platform can impose restrictions that tie a consumer's ability to purchase future SCO tokens at a favorable price to her past behavior. We consider in turn two simple mechanisms, one where the platform can design a SCO based on the full history of consumer's actions (a history-dependent mechanism), and a second where the platform can only design a SCO using current account information (a Markov mechanism), but cannot price discriminate using the individual's historical records. In practice, it might be hard to implement a full history-dependent mechanism for many reasons: costly data storage and processing, the complexity of the issuance design for each history, violation of privacy, or the consumer's sense of fairness. A Markov mechanism might be easier to implement and also more acceptable to

[88] Rogoff (2017)

[89] Memory has been pervasively used in business practice. CVS prints coupons for different products once consumers check out after scanning their CVS cards. Starbucks and McDonald's load customized special offers to their mobile apps based on the analysis of customers' past consumption data. Platforms can easily incorporate memory into tokens as a critical feature.

consumers.

In the extreme, the platform can sell one token in the initial ICO for $\frac{\beta p}{1-\beta}$, which is the entire present value of future platform consumption to the consumer, but then commit to distributing free tokens to any agent who tenders their token for consumption in any given period. This is, of course, tantamount a membership system where the lifetime dues are paid once and for all upfront.

Formally, consider a specific class of issuance policies where in any future SCO, a platform only issues tokens to consumers with $M-1$ tokens. Denote a as the ICO token price, b as the SCO token price, and define token issuance mechanism (X, Y, a, b) where X is the amount of tokens in the account, Y is amount of tokens to buy. [90] It is easy to check that "Buy M tokens in the ICO, and buy one token after a consumption shock in SCO" is an equilibrium strategy for consumers.[91] Using the account information, a platform can collect full future revenue with a finite amount of tokens.

2.6.1 History-dependent Issuance

A history-dependent issuance can achieve the first-best in the sense that a platform can punish any possible deviation from its issuance proposal. Under the case of perfect information, a history-dependent issuance policy enables the platform to gain full control of consumer choices.

We show that history-dependent issuance allows the maximum flexibility in the cash flow arrangement. Consistent with Kocherlakota (1998), memory expands the set of feasible allocations. To illustrate this point, we expand the Markov SCO price menu to a history-dependent SCO: If a consumer did not buy a token after a consumption shock before, the platform stops selling tokens to the consumer (that is (x, y, a, ∞) for any (x, y) pair); If a consumer buys a token after each shock in the history, the platform offer one token at price

[90] The extreme case discussed above can be written as follows: The price scheme of the ICO is $(0, M, \frac{\beta p}{1-\beta}\frac{1}{M}, b)$, $(0, x, \infty, b)$ if $x \neq M$. The price scheme of the SCO is $(M-1, 1, a, 0)$, (x, y, a, ∞) if $x \neq M-1$ or $y \neq 1$.

[91] First, consumers are indifferent between buying M tokens or never buying tokens. Thus, consumers have no incentive to deviate to "Not buying at all". Second, consumers cannot benefit from buying more or fewer tokens in the ICO since it costs more. Third, consumers would take free tokens in a SCO. Otherwise, consumers need to pay fiat money for consumption.

b (that is, SCO: $(M-1, 1, a, b)$, (x, y, a, ∞) if $x \neq M-1$ or $y \neq 1$). In a richer framework, a platform can design more sophisticated contingent issuance policies, but we leave this for future research.

We start from the participation constraint

$$Ma + \frac{\beta p}{1-\beta} b \leq \frac{\beta p}{1-\beta}$$

binds the minimum ICO price a with the maximum SCO price b. The minimum ICO price must be higher than the ICO token price with price menu.[92]

With history-dependent issuance, a consumer will be immediately excluded from the token market once she chooses not to purchase after any consumption shock.[93] Thus, the "now or never" inter-temporal constraint restricts consumers to buy one token right after a consumption shock if and only if

$$(1 + \frac{\beta p}{1-\beta}) b \leq [\frac{\beta p}{1-\beta(1-p)}]^{M-1} \frac{\beta p}{1-\beta}$$

The constraint implies that the SCO token price cannot exceed the consumption value of the marginal M^{th} token: $b \leq [\frac{\beta p}{1-\beta(1-p)}]^M$.[94] The minimum ICO token price is equal to the price under information-free price menu.

$$a = \frac{1}{M} \frac{\beta p}{1-\beta} (1 - [\frac{\beta p}{1-\beta(1-p)}]^M) \tag{15}$$

A history-dependent issuance essentially incorporates memory into each token issued to consumers. Each token is contingent on the sequence of past actions. The account history helps the platform to achieve all possible cash flow allocations. A digital currency with memory thus further improves the welfare of issuers; that is, data is extremely valuable for the issuer.

[92] $a > \frac{1}{M} \frac{\beta p}{1-\beta} [1 - (\frac{\beta p}{1-\beta(1-p)})^M] = P_{I,PM}$

[93] Under a Markov policy, a consumer can still stay in the token market with probability $1-p$.

[94] It is impossible to set the SCO price higher than the consumption value. Otherwise, consumers would prefer to pay with fiat money rather than buying tokens.

2.6.2 Markov Issuance (ICO+SCO)

Under a Markov issuance policy, the issuer can only design issuance based on current holdings, but cannot retrieve the full history of the consumer's behavior. Consumers may gamble by procrastinating the purchase of the SCO token because the issuer cannot punish a deviation based on their entire history. To incentivize consumers to buy the SCO token after a consumption shock, the issuer must design an issuance policy that satisfies a new "no procrastination" constraint:

$$(1+\frac{\beta p}{1-\beta})b \leq \beta \underbrace{[(1-p)(1+\frac{\beta p}{1-\beta})b}_{\text{No Consumption Shock: Still Use Tokens}} + \underbrace{p(\frac{\beta p}{1-\beta(1-p)})^{M-1}\frac{\beta p}{1-\beta}]}_{\text{Consumption Shock Arrives: Return to Fiat Money}}$$

The left-hand side is to "purchase" a token at a price b right after a consumption shock. The right-hand side is the payoff of procrastinating one period: without another consumption shock (probability $1-p$), a consumer can still purchase a token at the SCO price b; if another consumption shock arrives (with probability p), a consumer can never buy any token in the future and must make purchases with fiat money.[95] The "no procrastination" constraint pins down the maximum SCO price.[96]

$$a \leq \frac{1}{M}\frac{\beta p}{1-\beta}(1-\frac{\beta-\beta p}{1-\beta p}[\frac{\beta p}{1-\beta(1-p)}]^M) \tag{16}$$

Use of account information provides additional value to the platform in two ways.[97] First, the Markov issuance policy allows the platform to commit to a lower future SCO price in

[95] The present value of future spending in fiat money is

$$\sum_{i=M}^{\infty}(\frac{\beta p}{1-\beta p})^i = (\frac{\beta p}{1-\beta(1-p)})^M(\frac{1}{1-\frac{\beta p}{1-\beta(1-p)}}) = (\frac{\beta p}{1-\beta(1-p)})^{M-1}(\frac{\beta p}{1-\beta})$$

[96] The upper bound of the SCO price is lower than the consumption value of the M^{th} token.

$$b \leq \frac{\beta-\beta p}{1-\beta p}[\frac{\beta p}{1-\beta(1-p)}]^M < [\frac{\beta p}{1-\beta(1-p)}]^M$$

[97] An important caveat is that the analysis here assumes the platform can commit, if it cannot then, of course, it may be tempted to sell in later periods to consumers who choose not buy tokens initially.

order to boost the ICO price. But this only works if the platform can condition future sales on holdings. Second, the platform can continue to engage in short-term borrowing by selling tokens after every consumption shock.[98]

2.7 Heterogeneous Agents

In our framework, the consumption probability p is the cornerstone for the token price. The assumption maps into the reality that many technology companies take "Daily active users" (DAU) as a significant parameter to focus on. In this section, we relax the assumption of homogeneity and address the following three questions: Does consumer heterogeneity encourage or discourage token issuance? Is it more profitable to only cater to frequent consumers or to be more inclusive? Most importantly, does introducing heterogeneity overturn our conclusion that if tradability does not produce sufficient convenience yield, then platforms may find the issuance of non-tradable tokens more profitable?

Heterogeneity raises a number of issues including for example, how a platform can price discriminate. Our illustrative analysis suggests that in principle, however, heterogeneity will not overturn our core results. Nevertheless, we show that heterogeneity reduces the benefits of token issuance if the platform cannot price discriminate among consumers.

For simplicity, we assume a society consisting of half frequent buyers p_H and half infrequent buyers p_L. A platform aims to issue M tokens in total to all consumers, M_L per infrequent consumer at price P_L, and M_H per frequent consumer at P_H respectively. We define a pooling equilibrium (both types of buyers purchase a positive number of tokens at the same price) as the case where $P_H = P_L$. In separating equilibrium (or price discrimination equilibrium) the two types of consumers buy tokens at different prices (or one type of consumers stay out the token market entirely). The issuance quantity and consumption frequency follows

$$\frac{M_L + M_H}{2} = M$$

[98] If we write down the token sale revenue after each consumption shock, the amount of tokens purchased in ICO and SCO is $M, 0, ...0, M, 0, ..., 0$ with "no information" issuance of price menu. The Markov issuance policy allows the platform to front-load cash flow in all SCO periods by $M, 1, 1, 1, 1, 1, ...$

$$\frac{p_L + p_H}{2} = p$$

2.7.1 Non-tradable ICO with Price Only

If a platform cannot price discriminate, all consumers coordinate in a pooling equilibrium where price $\widetilde{P_{I,N}}$ is the same for everyone. The willingness to pay for the last token equals to the

$$(\frac{\beta p_i}{1-\beta(1-p_i)})^{M_i} = \widetilde{P_{I,N}} \quad i \in \{H, L\}$$

To issue M tokens, the corresponding price $\widetilde{P_{I,N}}$ must satisfy:

$$\frac{log(\widetilde{P_{I,N}})}{log(\frac{\beta p_L}{1-\beta(1-p_L)})} + \frac{log(\widetilde{P_{I,N}})}{log(\frac{\beta p_H}{1-\beta(1-p_H)})} = 2M$$

To simplify notation, we define function $f(p) = \frac{1}{log(\frac{\beta p}{1-\beta(1-p)})}$ and the non-tradable token price can be written as the following:

$$\widetilde{P_{I,N}} = e^{\frac{2}{f(p_L)+f(p_H)}M}$$

After introducing heterogeneity, the new effective discount factor of non-tradable tokens is $e^{\frac{2}{f(p_L)+f(p_H)}}$. Proposition 5 compares the new effective discount factor with the discount factor under heterogeneity $\frac{\beta p}{1-\beta(1-p)}(= e^{\frac{1}{f(p)}})$ as first defined in Section 3.1.

Proposition 5 (Heterogeneity of Non-tradable Tokens): The token price with agent heterogeneity is lower than the token price with homogeneous consumers of the same average consumption probability.

$$\widetilde{P_{I,N}} < P_{I,N}$$

Comments: Proposition 5 illustrates that agent heterogeneity leads to a lower average price for the same token issuance. We note, however, that the magnitude of price sacrifice caused by heterogeneity is not necessarily large since the curvature of function $log(\frac{\beta p}{1-\beta(1-p)})(\frac{1}{f(p)})$ is small for β and p near one (since log(x) is approximately linear around x=1). The effect of heterogeneity on revenue from fiat currency revenue (after the consumer uses up all her tokens) is ambiguous. Regardless, the magnitude of impact on cash revenue is only a second-order effect.[99]

Corresponding to our discussion of the homogeneous case, we next extend our analysis to the impact of agent heterogeneity on the following four mechanisms: a non-tradable ICO, a tradable ICO, a non-tradable ICO+SCO, and a tradable ICO+SCO. Lastly, we study a price menu mechanism.

2.7.2 Tradable ICO

With tradability, all consumers must receive the same token price in the ICO. Moreover, the token price must be expected to appreciate to generate the risk-free return required to induce agents of either type to hold more than one token. Frequent consumers gain more welfare surplus since they are more likely to use the tokens. The token price under heterogeneity is given by:

$$\widetilde{P_{I,T}} = \beta^{\frac{M-1}{p}}[(1-\beta^{\gamma}(1-P_L)^{\gamma})\frac{\beta p_L}{1-\beta(1-p_L)} + \beta^{\gamma}(1-P_L)^{\gamma}\frac{\beta p_H}{1-\beta(1-p_H)}]$$

where

$$\gamma = -\lfloor\frac{log(1+\frac{p_L}{2p_H})}{log(1-\frac{1}{2}p_L)}\rfloor$$

[99]Cash revenue with heterogeneity:

$$\frac{1}{2}\frac{\beta^*}{1-\beta^*}[p_H(\frac{\beta^* p_H}{1-\beta^*(1-p_H)})^{M_H} + p_L(\frac{\beta^* p_L}{1-\beta^*(1-p_L)})^{M_L}]$$

Cash revenue with homogeneity (where $p = \frac{p_L+p_H}{2}$):

$$\frac{\beta^*}{1-\beta^*}p(\frac{\beta^* p}{1-\beta^*(1-p)})^M$$

To quantify the impact of heterogeneity, we pick a set of parameters $p_H = 0.8, p_L = 0.4, \beta = 0.9, \beta^* = 0.8$ and plot the difference. The cash revenue difference is no more than 0.0005, while the total discounted revenue is 4 without token issuance. The difference from cash revenue is less than 1.25 basis points. We conclude that heterogeneity mildly discourages token issuance.

One can show two results: First, similar to the non-tradable case, heterogeneity reduces the token price for tradable tokens. With tradability, the token price must appreciate at the rate of interest regardless of the distribution of consumption probabilities.

Proposition 6 (Heterogeneity of Non-tradable Tokens): When $M = 1$, the token price with heterogeneity is lower than the price with homogeneity.

$$\widetilde{P_{I,T}} < P_{I,T}$$

Comments: Proposition 6 reveals that the token price under heterogeneity must be lower than the token price under homogeneity when only one token per person left in the economy. Heterogeneity can be viewed as a "friction" that limits the power of the platform to extract consumer surplus; frequent consumers retain positive surplus under token issuance. From the platform's perspective, revenue from token issuance is reduced by the consumer surplus if price discrimination is not feasible. We will return to price discrimination later.

Second, the token price of the tradable ICO is still lower than non-tradable ICO with heterogeneity, even if prices are both lower than the case of agent homogeneity. Propositions 7 and 8 speak to the point that our conclusion about tradability is robust to introducing agent heterogeneity.

Proposition 7 (Effective Discount Factor Dominance with Heterogeneity): Under heterogeneity, the effective discount rate of non-tradable ICO tokens is still higher than that of tradable ICO tokens.

$$\beta^{\frac{1}{p}} < e^{\frac{2}{f(p_L)+f(p_H)}}$$

Proposition 8 (ICO Price Dominance with Heterogeneity): When $M = 1$, the token price with tradability is lower than the non-tradable token price under heterogeneity.

$$\widetilde{P_{I,T}} < \widetilde{P_{I,N}}$$

Comments: Proposition 7 is parallel to the Proposition 1 under the agent heterogeneity, implying that the tradable ICO price discounts faster than the non-tradeable ICO price as the quantity of tokens issued increases.[100] Proposition 8 proves that the tradable token price is lower than the non-tradable token price when $M = 1$ (Recall that token prices are the same for tradable and non-tradable when $M = 1$ under homogeneity). Proposition 8 is unique to the agent heterogeneity case since trading still occurs between high-type and low-type when less than one token circulates in the economy. Thus, as in the homogeneity case, the tradable token price is lower for any possible quantity of token issuance. Our core tradability result is robust to heterogeneity of consumption probabilities.

2.7.3 Tradable/ Non-tradable ICO+SCO

Similar to the homogeneous case, with tradability, there is no way to improve on a "token-in-advance" policy (selling a tokens one period ahead). Frequent consumers are willing to pay $\frac{\beta p_H}{1-\beta(1-p_H)}$ and infrequent consumers are willing to pay $\frac{\beta p_L}{1-\beta(1-p_L)}$. The new element here is having to choose between issuing to frequent consumers with a high price and issuing to everyone with a low price.

Pooling Equilibrium: Low price, broad consumer base: If the platform wants everyone to buy its tokens, the price needs to be $\frac{\beta p_L}{1-\beta(1-p_L)}$.[101]

Under a pooling equilibrium, consumption heterogeneity makes the issuer worse off since the infrequent consumers drag down the token price.

$$\frac{\beta p_L}{1-\beta(1-p_L)} < \frac{\beta p}{1-\beta(1-p)}$$

Separating Equilibrium: High price, narrow consumer base: If the issuer only

[100] With tradability, the effective discount rate is always $\beta^{\frac{1}{p}}$ regardless of the consumption probabilities. Without tradability, the effective discount rate is lower with consumption heterogeneity as shown in Proposition 6. Thus, Proposition 7 is a tighter inequality than Proposition 1.

[101] In the pooling equilibrium case, the platform may not want to issue the token one period ahead if

$$\frac{\beta p_L}{1-\beta(1-p_L)} < \frac{1}{2}\left(\frac{\beta^* p_L}{1-\beta^*(1-p_L)} + \frac{\beta^* p_H}{1-\beta^*(1-p_H)}\right)$$

wants to cater frequent consumers only, the token price will be offered at $\frac{\beta p_H}{1-\beta(1-p_H)}$.[102] Intuitively, the platform should cater to frequent consumers (set a high price that only frequent consumers take up) only when there is a significant gap between the probabilities for high and low types. The issuer chooses the separating equilibrium if and only if

$$\frac{\beta p_L}{1-\beta(1-p_L)} < \frac{1}{2}(\frac{\beta p_H}{1-\beta(1-p_H)} + \frac{\beta^* p_L}{1-\beta^*(1-p_L)})$$

Proposition 9 (ICO+SCO Revenue Dominance with Heterogeneity) :
Heterogeneity reduces the discounted revenue of ICO+SCO issuance.

$$\widetilde{R_S} < R_S$$

Comments: Proposition 9 verifies that the consumption probability heterogeneity causes the platform to earn strictly less revenue regardless of the issuance policy. Under a pooling equilibrium, infrequent consumers reduce the token price and make issuers unable to extract surplus from frequent consumers. Under a separating equilibrium, the issuer has to forgo half the population in the token issuance.

2.7.4 Price Menu Policies

The price menu mechanism enables the separating equilibrium where frequent consumers buy more tokens at a higher average price, and infrequent consumers buy fewer tokens at a lower average price (or even excluded in the token market when p_L is small enough).

[102] The welfare gain from token issuance is only from frequent consumers,

$$\frac{1}{2}(\frac{\beta p_H}{1-\beta(1-p_H)} - \frac{\beta^* p_H}{1-\beta^*(1-p_H)})$$

The revenue under separating equilibrium is

$$g(p_H, p_L) = \frac{1}{2}[\underbrace{\frac{1-\beta^*(1-p_H)}{1-\beta(1-p_H)}\frac{\beta p_H}{1-\beta^*}}_{\text{Frequent Consumers with tokens}} + \underbrace{\frac{\beta^*}{1-\beta^*}p_L}_{\text{Infrequent Consumers without tokens}}$$

]

2.8 Conclusion

In this paper, we have studied to what extent large retailer platforms might have an advantage in issuing non-interest bearing digital tokens (currencies) by leveraging the fact that there are many consumers who are regular buyers, and who might find in-platform tokens appealing and convenient, while potentially both saving the platform fees paid to financial intermediaries as well as generating revenues of their own through a net interest margin.

Our core finding is that it many cases, it may be advantageous to the platform to issue non-tradable tokens rather than tradable ones, even if that means foregoing ideas of creating a prototype currency, unless the prototype currency can be expected to create significant convenience yield. Non-traded tokens give the platform the ability to implement more sophisticated pricing strategies (for example a price menu approach), and to incorporate memory features.

It is important to recognize that at the end of the day, a great deal depends on regulation, taxation, and other policy choices affecting not only technology companies but also financial firms. Nevertheless, the simple benefit for platforms we look at here (net interest margin) is certainly an important one, especially if, as we assume, digital tokens give retail platforms access to the same kind of low interest-rate lenders that banks have so long profited from.

Our analysis has focused mainly on non-interest bearing tokens; if tokens can pay market interest, this can solve many of the problems we have analyzed, and this is certainly one solution. However, as discussed in the text, a pledge to pay market interest has its own issues, with implications for taxation, regulation, credibility, governance, and implementation.

The model presented here allows one to analyze a hierarchy of platforms depending on the frequency with which the consumer accesses them, and potentially also the size of transactions, and therefore how such differences might affect platform strategies when it comes to token/coin issuance. Our analysis aims to be the first stab in understanding token issuance mechanisms but does not intend to horse-race token with traditional financing approaches, like bonds or equity. The huge range of crypto-currencies that have been issued to date, with ties to everything from social networking to real estate provide fertile ground for empirical analysis. In principle, it is also possible to exploit data on related token devices from the pre-digital commerce era, including green stamps, loyalty points etc. although as we have previously noted, the technology of this era did not allow for using data in the same way as today, and the issue of ICOs is new.

The last part of our paper introduces a number of issues related to heterogeneity, which opens up a host of interesting questions for future research. Loyalty programs and gift cards have been around for a long time and are already economically significant, but new generations of redeemable platform tokens are in an explosive growth phase and are set to play an increasing role in payments in the monetary economics of the future.

Proposition Proofs

Proof of Proposition 1: Effective Discount Factor Dominance

To show $\beta^{\frac{1}{p}} < \frac{\beta p}{1-\beta(1-p)}$, we rewrite the inequality linearly as

$$\Longleftrightarrow \beta p > \beta^{\frac{1}{p}} - \beta^{1+\frac{1}{p}}(1-p)$$

Then, we define a function $\omega(\beta)$ and show $\omega(\beta) > 0$ in the range of $p \in (0,1)$:

$$\omega(\beta) = \beta p - \beta^{\frac{1}{p}} + \beta^{1+\frac{1}{p}}(1-p)$$

First, it is easy to find that $\omega(0) = 0$ and $\omega(1) = 0$. Then, we characterize $\omega(\beta)$ with the first-order and second-order derivatives:

$$\omega'(\beta) = p - \frac{1}{p}\beta^{\frac{1}{p}-1} + (1+\frac{1}{p})\beta^{\frac{1}{p}}(1-p)$$

$$\omega''(\beta) = \frac{1}{p}(\frac{1}{p}-1)\beta^{\frac{1}{p}-2} + (1+\frac{1}{p})\frac{1}{p}\beta^{\frac{1}{p}-1}(1-p) = \beta^{\frac{1}{p}-2}\frac{1}{p}(\frac{1}{p}-1)[1-(1+p)\beta]$$

Note that $\omega'(0) = p > 0$ and $\omega'(1) = 0$. From the second-order derivative ($\omega'' = 0 \Longleftrightarrow \beta = \frac{1}{1+p}$), we find that $\omega'(\beta)$ is monotonically decreasing when $\beta < \frac{1}{1+p}$ but increasing when $\beta > \frac{1}{1+p}$.

Then, we show the existence of a unique β such that $\omega'(\beta) = 0$. Existence: $\omega'(0) = p > 0$. $\omega''(1) < 0$ implies that $\omega'(1-\epsilon) < 0$ where ϵ is a positive infinitesimal. By the continuity, there must exists a β $\omega'(\beta) = 0$. Uniqueness: If there is more than one root, say $0 < \beta_1 < \beta_2 < 1$, then $\omega'(\beta_1) = \omega'(\beta_2) = \omega'(1) = 0$. By the continuity, there must exist $\widehat{\beta_1}$ and $\widehat{\beta_2}$ so that $\omega''(\widehat{\beta_1}) = \omega''(\widehat{\beta_2}) = 0$ and $\beta_1 < \widehat{\beta_1} < \beta_2 < \widehat{\beta_2} < 1$. However, we know that $\beta = \frac{1}{1+p}$ is the only root for $\omega''(\beta) = 0$ in the range of $(0,1)$. This violation implies a unique solution to $\omega'(\beta) = 0$.

Last, we show that $\omega(\beta) > 0$ holds when $\beta \in (0,1)$. $\omega'(0) = p > 0$ implies $\omega(\epsilon) > 0$ for a positive infinitesimal ϵ. If there is a β_3 where $\omega(\beta_3) \leq 0$, we can find a $\beta_4 \in (\epsilon, \beta_3)$ so that $\omega(\beta_4) = 0$. $\omega(0) = \omega(\beta_4) = \omega(1) = 0$ implies at least two roots for $\omega'(\beta) = 0$. It violates the uniqueness of the solution to $\omega'(\beta) = 0$.

To give a graphical illustration, we plot the gap between the two effective discount factors as a function of β with $p = 0.9$ as in Figure 5.

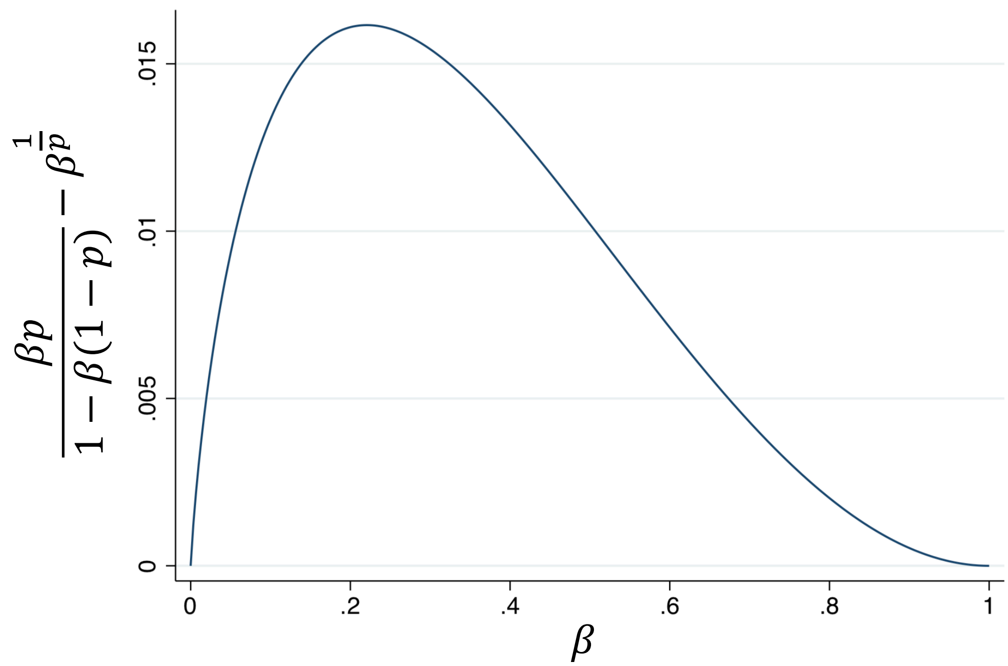


Figure 5 plots the difference between effective discount factors for the non-tradable and tradable tokens as a function of β. The probability of consumption shock is set as $p = 0.9$.

Proof of Proposition 4: Non-tradable ICO dominance over ICO+SCO

We consider three corner cases $\beta^* \to 0$, $p \to 0$, and $\beta^* \to \beta$:

Case 1 $\beta^* \to 0$: $max_M R_{I,N} - R_S = max_M M(\frac{\beta p}{1-\beta(1-p)})^M - \frac{\beta p}{1-\beta(1-p)} \geq [M(\frac{\beta p}{1-\beta(1-p)})^M]|(M=1) - \frac{\beta p}{1-\beta(1-p)} = 0$

When $\beta^* \to 0$, ICO dominates because the issuer does not value future revenue at all. "Token-in-advance" limits the issuer's ability to collect token revenue in the ICO period.

Case 2 $p \to 0$: The gain to issue the second token is only second-order (a constant multiplies p^2):

$$(\frac{\beta p}{1-\beta(1-p)})^2 - (\frac{\beta^* p}{1-\beta^*(1-p)})^2 \approx [(\frac{\beta}{1-\beta})^2 - (\frac{\beta^*}{1-\beta^*})^2]p^2$$

.

But the loss is first order (a constant multiplies p):

$$(\frac{\beta p}{1-\beta(1-p)})^2 - (\frac{\beta p}{1-\beta(1-p)}) \approx -\frac{\beta}{1-\beta}p$$

The first-order loss is larger than the second-order gain. Thus, the optimal non-tradable ICO token issuance is one. ICO+SCO strictly dominates non-tradable ICO with one token outstanding because SCO can frontload cash flow and increase revenue by $p[\frac{\beta p}{1-\beta(1-p)} - \frac{\beta^* p}{1-\beta^*(1-p)}]$ in every future period.

Case 3 $\beta^* \to \beta$: The gain from the second token issuance is close to zero. The loss is $(\frac{\beta p}{1-\beta(1-p)})^2 - (\frac{\beta p}{1-\beta(1-p)}) \approx -\frac{\beta}{1-\beta}p < 0$. Thus, the optimal non-tradable ICO token issuance is also one. Similarly, the ICO+SCO dominates the non-tradable ICO in this case.

3 Converging to Convergence

3.1 Introduction

Studies in the 1990s found little evidence of convergence, and if anything, the opposite: rich countries growing faster than poor, resulting in divergence (Barro (1991); Pritchett (1997)). This led to two responses: first, a rejection of the neoclassical model and the development of endogenous growth theory, variants of which predicted divergence (Romer (1990)); second, an emphasis on underlying determinants of steady-state income, such as policies, institutions, and human capital, leading to growth regressions and tests of convergence *conditional* on them (Durlauf et al. (2005)). Subsequent research used historical variation in institutions to identify their causal effects on economic outcomes, emphasizing their persistence over time (Acemoglu et al. (2001); Michalopoulos and Papaioannou (2013); Dell (2010)).

To update the stylized facts of convergence, we revisit the empirical exercise with twenty-five years of additional data, relative to the literature's peak. We consider global trends in income and growth, as well as factors that might determine them, such as policies, institutions, human capital, and culture. Far from being static, there have been substantial changes since the late 1980s, both in the outcomes themselves and in the relationships between them. While we do not provide a full analysis of the reasons, or causal determinants, we think this is still useful, as any understanding of development should match the cross-country patterns of income, growth, and their correlates.

We begin with absolute convergence – poor countries growing faster than rich, unconditionally – and document *convergence towards convergence* in income per capita. There has been a steady trend towards convergence since the late 1980s, leading to absolute convergence since the turn of the century, precisely when empirical tests of convergence fell out of fashion. In terms of magnitudes, from 1985-1995 there was divergence in income per capita (PPP-adjusted) at the rate of 0.5%, while from 2005-2015 there was convergence at a rate of 0.7%.[103] Looking further back to 1960, when the widespread collection of national income data began, the trend in convergence was initially flat, with neither convergence nor divergence, followed by a decade of a trend towards *divergence* in the late 1970s and early 1980s.

Breaking down the trend towards absolute convergence since the late 1980s by subsets of countries provides support for several potential explanations. The richest quartile of countries had the highest growth rate of all quartiles in the 1980s and then switched position entirely to have the lowest growth rate since 2000. The shift was driven both by a slow-down of growth at the frontier - the richest quartile of countries experienced flat growth in the 1990s and then a growth slowdown since 2000 – and faster catch-up growth - the other three quartiles experienced a substantial acceleration in growth in the 1990s. Since the mid-

[103]Our base specification uses income per capita adjusted for Purchasing Power Parity, from the Penn World tales, but a similar trend is found using income per capita from the World Development Indicators, measured in constant 2010 USD, and also when using income per worker.

nineties, there have been fewer disaster countries – countries that are both poor and experiencing very low or even negative growth. Accounting for them by excluding countries with prolonged negative growth rates, dampens the trend towards convergence, but only slightly, and moreover it does so by removing the trend towards divergence in the late 1970s and early 1980s, suggesting that trend was caused by such disasters. The trend is also not driven by any one specific region or set of countries, and convergence becomes stronger upon removing Sub-Saharan Africa or the bottom quartile of the income distribution, suggesting some countries may still be being left behind.

We then turn to global trends in potential determinants of growth and steady-state income, such as policies, institutions, human capital, and culture. We divide such potential correlates of income and growth into four groups: *enhanced Solow fundamentals* – investment rate, population growth rate, and human capital – variables which are fundamental determinants of steady state income in the enhanced Solow model (Mankiw et al. (1992)); *short-run correlates*, other policy and institution variables considered by the 1990's growth literature which may vary at relatively high frequency; *long-run correlates*, institutions and their historical determinants which do not change or which only change slowly, which have been the focus of the recent institutions literature, as well as geographic correlates of income; and *culture*. Far from being static, we find that many correlates have undergone large changes and themselves converged substantially across countries, towards those of rich-countries.

For short-run correlates, we examine 27 variables in four categories: political institutions, governance quality, fiscal policy, financial institutions. To tie our hands over which variables we include, we started from a list of variables commonly used in growth regressions, from the Handbook of Economic Growth chapter on "Growth econometrics" (Durlauf et al. (2005)). We then constrained ourselves to those variables which were available for at least 40 countries by 1996, and we chose to focus on the period 1985-2015 as a compromise between the number of countries and the number of time periods. Among the 32 variables considered in enhanced Solow fundamentals and short-run correlates, we find significant beta-convergence - institutions improving faster on average in countries where they are poorer - in 29. Only credit to the private sector has diverged over time. 21 variables have sigma-converged - the cross-sectional variance has decreased over time - while five have sigma-diverged.

While convergence was unlikely or impossible for long-run correlates, and we do not time variation to test for it, we do find evidence of convergence in culture. Using the different rounds of the World Value Survey, we find that while culture does show persistence, eight out of the ten cultural variables we consider have been converging since 1990. For example, views on inequality, political participation, the importance of family, traditions, and work ethics have all been converging. While limited, the results of the exercise are consistent with numerous papers in sociology and psychology (Inglehart and Baker (2000) and Santos et al. (2017))

Are these two findings, the trend towards convergence in income and the convergence of many of the correlates of income and growth, since the late 1980s, related? On the one hand, an extensive empirical literature argues that correlates such as institutions are important for economic development (Glaeser et al. (2004); Acemoglu et al. (2005)), and the convergence literature itself moved towards convergence *conditional* on correlates (determinants of the steady state), suggesting causality could run from converging correlates to converging growth. On the other hand, modernization theory suggests that causation may run the other way, with converging incomes causing policies, institutions, and culture to converge. Recent literature uses instrumental variables to provide evidence on both directions, using historical variation in institutions (or other instruments) to establish their effect on long-run growth (Acemoglu et al. (2001); Michalopoulos and Papaioannou (2013); Dell (2010); Acemoglu et al. (2019)), and using instruments for income to test modernization theory (Acemoglu et al. (2008)). These studies build on earlier analysis which focused on stylized facts, either from growth regressions (Barro (1996); Sala-i Martin (1997); Durlauf et al. (2005); Rodrik (2012)) or from the observation that rich countries share a common set of policies and institutions: they are more democratic, less corrupt; they have robust financial systems, more effective governance, better social order, etc. It is these earlier analyses - of empirical cross-country relationships between income and correlates and between growth and correlates - which we return to and update, with twenty years more data and by adding in the long-run institutions and culture which have been the focus of the recent growth literature. While our analysis is purely descriptive, it is motivated by whether the changes in income, growth, and their correlates are consistent with a causal link from correlates to growth, or a causal link from income to correlates, or both?

The cross-sectional relationships between income and the correlates have changed in levels, but their slopes have mostly remained stable, despite large changes in both income and the short-run correlates. Is this evidence in support of or against Modernization theory? On the one hand the joint convergence in income and in correlates appear to have happened consistently with their baseline cross-sectional relationships, such that the slope of the cross-country regressions have changed remarkably little. Among 32 Solow and short-run correlates, there is a correlation of 0.72 between the cross-sectional correlate-GDP slope in 1985 and in 2015. Moreover, *on average* Solow and short-run correlates have changed as much as would have been predicted by the changes in income, given the baseline cross-country relationship between the two. On the other hand, *per correlate*, these predictions explain relatively little of the observed changes in the average levels of Solow and short-run correlates. For long-run correlates and culture, unsurprisingly the correlate-income relationships have changed even less.

More strikingly, growth regression coefficients have shrunk across the period. The coefficients of the Solow fundamentals have remained the most stable, with a correlation of 0.39 between 1985 and 2005. The coefficients of short-term correlates have changed the most, such that there is almost no correlation in coefficients between the periods. For example, in 1985, one additional score in Freedom House political predicted 0.6% higher annual GDP growth for the subsequent decade, yet the predictive power is negligible in the decade 2005-2015. Long-run correlates and culture fall somewhere between the two, with coefficients which are somewhat stable across the periods (correlations of around 0.3), although on average they also shrank.

Has the trend to absolute convergence occurred because absolute convergence has converged to conditional convergence, or because conditional convergence itself has become faster? We can gain intuition for what has happened by using the formula for omitted variable bias, which says that the gap between absolute and conditional convergence (when conditioning on a single variable) is the correlate-income slope multiplied by the growth regression coefficient. The reduction of both the magnitude of growth coefficients and their correlation with correlate-income slopes *is* associated with a substantial shrinking in the gap between absolute convergence and conditional convergence. Moreover, the trend in absolute convergence can be explained by this shrinking in the gap with conditional convergence – there is no obvious trend in conditional convergence itself, which held throughout the period.

These results suggest an interpretation that is consistent with neoclassical growth models. Conditional convergence has held throughout the period. Absolute convergence did not hold initially, but, as policies, institutions, and human capital have improved in poorer countries, the difference in institutions across countries has shrunk, and their explanatory power with respect to growth and convergence has declined. As a result, the world has converged to absolute convergence because absolute convergence has converged to conditional convergence.

However, this narrative leaves a key question unanswered: why did the growth regression coefficients change? A relatively interventionist interpretation is that policies and institutions used to matter, but now that they have converged, they matter less. For example, perhaps really bad institutions are bad for growth, but so long as institutions are not disastrous, they matter much less. So long as countries have reasonable institutions, there will be convergence. A less favorable interpretation is that policies and institutions have never really mattered in growth regressions: earlier specifications suffered from an overfitting problem and are now failing an out-of-sample test using subsequent data. This would also explain the shrinking of the gap between absolute and conditional convergence, but then the cause of the trend towards absolute convergence remains unknown.

This paper describes trends in major macro-economic variables and the relationships between them, some of which have changed substantially in the last twenty years. The goal is descriptive, not causal. The first literature we contribute to is that regarding convergence, which was at its apex in the 1990s. Despite absolute convergence being a central prediction of foundational growth models, multiple papers found no evidence for absolute convergence in incomes across countries (Barro (1991); Pritchett (1997)), although evidence of convergence within countries (Barro and Sala-i Martin (1992)) and across countries conditional on similar institutions. More recently there have been several important additions to these findings. Rodrik (2012) looks specifically at manufacturing and shows that within manufacturing, there has been absolute convergence. Grier and Grier (2007), a paper closely related to ours, also considers convergence in both income and in policies and institutions from 1961-1999. They contrast convergence in policies and institutions with divergence in incomes, arguing that this difference is hard to reconcile with neoclassical growth models. We agree with their conclusion for the period 1960-1990, but benefit from twenty years of additional data, and argue that convergence changed around 1990. The trend towards convergence since then, resulting in convergence since 2000, is consistent with models of neoclassical growth and inconsistent with a class of endogenous growth theory models which predict divergence, such as AK models.

This is not the only paper to revisit the question of convergence with updated data. Roy et al. (2016), in particular, make the point that there has been absolute convergence in the last 20 years and, in concurrent work to ours, Patel et al. (2021) emphasize how this is in contrast to the previous stylized facts about convergence. Johnson and Papageorgiou (2020), in contrast, also uses the latest data and concludes that there is still no absolute convergence. The difference results in part from Johnson and Papageorgiou (2020) considering convergence from a fixed base date (1960), while we consider the trend in convergence over a moving time interval, and in part because we are willing to speculate that the trend in the last twenty-five years represents a fundamental change. Indeed, while we find a sustained trend towards convergence, we only find actual convergence for a relatively short period, whilst historically divergence has been the norm for several hundred years Pritchett (1997). Whether the recent shift to convergence does reflect an underlying, long-term change, or whether it is just transitory due to, for example, higher commodity prices, is an important question. We argue that the gradual trend towards convergence over twenty-five years makes such transitory explanations less likely, we propose possible explanations for a long-term change, and we show that the trend is robust to excluding major commodity exporters.

The paper also adds to the literature on the effects of culture and institutions. Recent papers use historical variation to identify the effect of institutions and culture on income, using either instruments (Acemoglu et al. (2001); Algan and Cahuc (2010)) or spatial discontinuities (Dell (2010)), and generally find that both play a central role. Such an approach can only identify the effect of persistent institutions and cultural traits, and while some, such as legal systems and trust, have deep historical roots and appear to change very slowly (Michalopoulos and Papaioannou (2013)), many change rapidly. There is no contradiction in institutions both having a long-run effect and being subject to recent change. For example, gender roles have deep and important historical determinants (Alesina et al. (2013)), but they have also changed substantially in the last 50 years, differentially across countries. While historical determinants continue to persist, we should also remain open to asking how recent changes in policies and institutions have affected growth, especially when considering policy changes. Our growth regressions exercise also provides an out-of-sample test of sorts for the predictive power of policies and institutions. With a limited sample size and many potential covariates, the growth regressions literature is vulnerable to overfitting. Events since the publication of earlier papers provides a (limited) out-of-sample dataset.

Finally, in studying changes to, and convergence in, policies, institutions, and culture, the paper adds to expansive literatures in political science, sociology, and psychology whereby the diffusion and convergence of numerous policies, institutions and cultural traits have been documented and studied (Dobbin et al. (2007)).[104] Some of the changes in correlates have been gradual, possibly consistent with modernization theory (Acemoglu et al. (2008); Inglehart and Baker (2000)), and indeed we do find that on average changes in correlates are consistent with predictions from income growth, based upon the cross-country relationship. However, many recent changes in policies and institutions are dramatic, such as global trends in the adoption of VATs, or marriage equality, or the Me Too movement, which may be better thought of as technology adoption through information diffusion. This technology diffusion may be passive or may, for example, result from the work of International Organizations, who provide norms and information on perceived best practices (Clemens and Kremer (2016)), and sometimes directly coerce the adoption of different policies through conditionality. For example, the "Washington Consensus" encouraged lowers tariffs, lower inflation, and more democracy, all of which have been broadly adopted since. In a closely related paper, Easterly (2019) argues that such "Washington Consensus" reforms may have been better for growth than previously believed, as growth has been higher recently in countries which adopted them. Finally, convergence and diffusion of culture are central topics in sociology and psychology. Two recent examples studying them using the World Value Surveys (among other data sources) as we do, are Inglehart and Baker (2000) and Santos et al. (2017).

The paper proceeds as follows. In section 2, we present the results on absolute convergence in income per capita and document what we interpret as a trend towards convergence since the 1990s. In section 3, we consider what has happened to correlates of growth - policies, institutions, human capital, and culture - across the world and document considerable convergence across multiple dimensions. In section 4, we relate the trend towards convergence in income and the convergence in the correlates of growth, first considering the implications for the cross-sectional relationship between income and correlates and modernization theory, and then turning to the implications for conditional convergence, growth regressions, and neoclassical growth theory. Section 5 concludes.

3.2 Convergence in income

Neoclassical growth models predict convergence towards steady-state income: poor countries should catch up with rich countries, at least among countries with similar underlying determinants of steady-state income. Empirical tests in the 1990s of *absolute* convergence - convergence across countries without conditioning on determinants of steady state income - found little evidence for it: if anything, rich countries were growing faster than poor (Barro 1991). We begin by revisiting these tests of absolute convergence, with 25 additional years of data. We use the same data sources and focus mainly on β-convergence, defined

[104] The social science literature on the diffusion of policies has proposed four theories for policy diffusion: social construction, coercion, competition, or learning. See Dobbin et al. (2007) for a review.

below.[105]

Notes: This figure plots, by decade, the raw scatter plots for the decade's β-convergence regression, as well as the regression line itself.

$$100\frac{log(GDPpc)_{i,t+10} - log(GDPpc)_{i,t}}{10} = \alpha_t + \beta_t log(GDPpc)_{i,t} + \epsilon_{i,t}$$

Figure 3: Income convergence by decade
The income measure is income per capita, adjusted for PPP, from the Penn World Tables v10.0. The sample is all countries for which data is available, excluding those with a population less than 200,000 or for whom natural resource rents for > 75% of their GDP. Data availability means that the number of countries is growing over time. For 2007, the period considered in 2007-2017.

3.2.1 Empirical setup: measuring convergence

The convergence literature in the 1990s used three different datasets. First, standard cross-country sources such as the World Development Indicators and the Penn World Tables, which covered a sizeable

[105]Parallel results for σ-convergence are in Figure 3 Panel (b) and Appendix Figure C.3 Panel (b) with a fixed country sample

span of countries from the 1960s onwards. Second, the Maddison dataset, which collected many sources of data to derive income per capita going back much further in time, for a smaller set of countries, which showed that divergence had been the norm for several hundred years (Pritchett 1997. Third, within-country panel datasets, to look at convergence within countries. For example, Barro and Sala-i Martin (1992) examined convergence within the US.

Our goal is to document what has happened to global cross-country convergence since the heyday of the literature in the 1990s. As such, we use the standard cross-country data sources, which cover 1960-present. In the main specification, we use the GDP per capita, adjusted for Purchasing Power Parity (PPP) from the Penn World Tables v10.0.[106] It is an unbalanced panel, as for many countries GDP per capita data only becomes available part way through the period. Nevertheless, we use the unbalanced panel for our main specification so as not to drop many of the poorer countries which become available later in the period (we also show robustness to using balanced panels, which make little difference to our results). We also drop very small countries and those which are extremely reliant on natural resource rents, as is common in studies of convergence. Specifically, we drop countries whose maximum population during the period was $< 200,000$, and those for whom rents from natural resources accounted for at least 75% of GDP (as reported in the World Development Indicators) at some time during the period.

We examine both β-convergence and σ-convergence. β-convergence is when poor countries grow faster on average than rich, while σ-convergence is when the cross-sectional variance of (log) income per capita is falling over time. The relationship between the two notions of convergence is well documented (Barro and Sala-i Martin 1992; Young et al. 2008). We focus on β-convergence for most of the analysis, with equivalent results for σ-convergence reported in the Appendix.

β-convergence β-convergence is when poorer countries grow faster on average than richer countries. Specifically, at a given time period t, it is when the country-level regression

$$log(GDP_{i,t+\Delta t}) - log(GDP_{i,t}) = \alpha + \beta log(GDP_{i,t}) + \epsilon_{i,t}$$

has a negative β coefficient, where $log(GDP_{i,t})$ is Log GDP of country i at time t. To show how β-convergence has changed over time, we plot β_t vs. t, where β_t comes for the following country-year level regression, clustered at the country level (μ_t is a year fixed effect on growth):

$$log(GDP_{i,t+\Delta t}) - log(GDP_{i,t}) = \beta_t log(GDP_{i,t}) + \mu_t + \epsilon_{i,t}$$

Much of the existing empirical convergence literature plots how β varies when holding the starting

[106]Specifically, for growth rates we use the variable "rdgpna", real GDP at constant 2017 national prices (2017 USD), and for growth levels we use "rdgpo", output-side real GDP at chained PPPs (2017 USD), as recommended by the PWT user guide.

point t fixed (often at 1960) and varying the end point, $t + \Delta t$. Since we are interested in how the process of convergence may itself have changed over time, we instead hold Δt fixed and vary t. In the main specification we use 10-year averages, i.e. $\Delta t = 10$.[107]

Econometric considerations There is a large literature on the tradeoffs of different econometric specifications to test for convergence, summarized in Durlauf et al. (2005). We follow the most standard approach, testing for β convergence using OLS with fixed-effects for year, clustered at the country level. One concern is measurement error, which may drive towards convergence through mean reversion. This is one reason for which we also look at σ convergence. Another issue is data availability: income data only becomes available for some countries long after the start date. Our base analysis using an unbalanced panel, but we discuss robustness below.

3.2.2 Results: converging to convergence

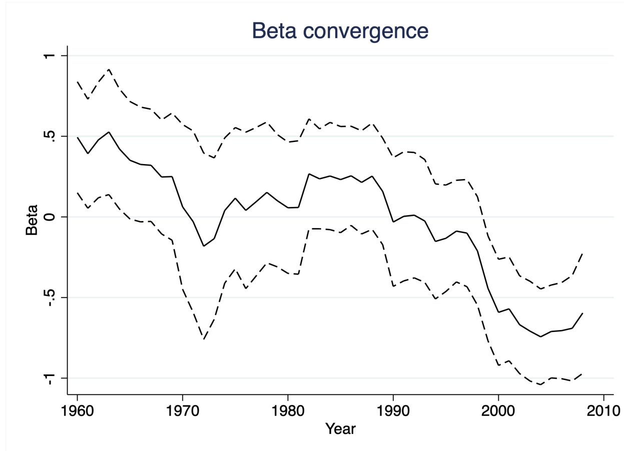
Figure 3 shows the scatter plot and regression of Section 3.2.1 for each decade since 1960. Convergence corresponds to a negative slope, and the shift to convergence since 2000 can clearly be seen in the raw data. Figure C.2 presents summary boxplots of these basic scatter plots, plotting the average growth by income quintile for each decade.

Figures 4a and 4b show the β- and σ-convergence coefficients from these regressions over the whole period 1960-2007. The first striking result is that there has been absolute convergence since the late 1990s, precisely when the best-known empirical tests of convergence were published. The point estimate for β-convergence becomes negative in the early 1990s, becoming significant in the late 1990s and staying significant since. Table 11 shows a point estimate of -0.59 in the 2000s, and -0.69 in the ten years after 2007, the most recent period we can consider. σ-convergence, represented by a negative slope in Figure 4, started slightly later, with the standard deviation in GDP per capita falling since the early 2000s. The difference in timing is consistent with β-convergence being a function of subsequent 10-year average growth.

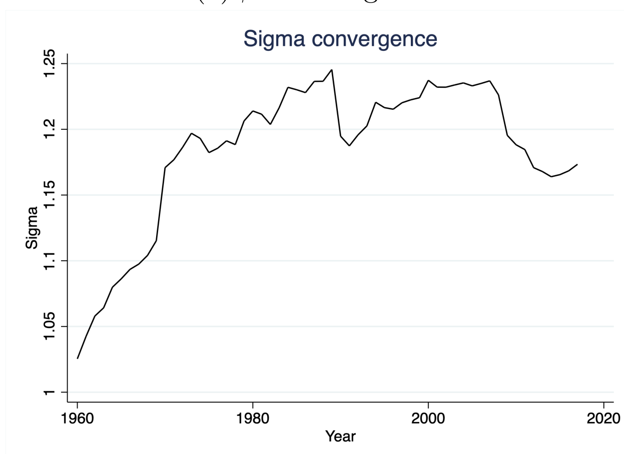
The second result is that there has been a trend towards β-convergence - converging to convergence – since 1990. The coefficient started at around 0.5 in 1990 and has trended down towards -1 today. Looking further back to 1960, initially there is no clear trend, and then there is a trend towards *divergence* in the 1980s.[108] Table 11, Column (2), reports the results of our basic absolute convergence regression, Equation 3.2.1, with the addition of a linear year variable interacted with $log(GDP_{i,t})$. The interaction terms, representing the "convergence towards convergence", is negative and significant, with a point estimate of -0.024. The trend towards convergence is also apparent in the σ-convergence figure, where it is represented by a gradual

[107]The dependent variable is the annualized growth — the geometric average growth rate in the next decade.

[108]In subsequent robustness exercises, not using PPP adjustments, the trend looks more like a steady trend towards convergence since 1960, except for a major reversal in the 1980s



(a) $\beta-$convergence.



(b) $\sigma-$convergence.

Figure 4: Trend in income convergence, 1960-2007

Notes: These figures show the trend in convergence from 1960 to 2007. Figure a) plots the β-convergence coefficient, for growth in the subsequent decade, over time. It is the coefficient from regressing, across countries, the average growth in GDP per capita in the next decade (in %) on the log of GDP per capita, with year fixed effects, and with standard errors clustered by country. Income per capita is adjusted for PPP and comes from the Penn World Tables, v10.0. The sample is growing over time, as detailed in Figure 3. Figure b) plots the evolution over time of the cross-country standard deviation in GDP per capita. *sigma*-convergence corresponds to a negative slope of the plot. The plot shows concavity, resulting in a negative slope recently, corresponding to converging to convergence. Equivalent panels using balanced panels are in Figure C.3.

decrease in slope, i.e. concavity of the plot.

There are several natural robustness questions. Is the change driven by panel imbalance, in particular the larger number of poor countries entering the panel over time? Are the results robust to the averaging period? Do they depend on the macroeconomic dataset used? In the following we show that results are robust to these concerns.

Table 11: Converging to convergence. Absolute convergence 1960-2017

	Average annual growth in next decade		
	(1)	(2)	(3)
log(GDPpc)	-0.198*	0.468**	
	[0.109]	[0.192]	
log(GDPpc) * (Year-1960)		-0.024***	
		[0.005]	
log(GDPpc) * 1960s			0.494***
			[0.176]
log(GDPpc) * 1970s			0.062
			[0.261]
log(GDPpc) * 1980s			0.057
			[0.208]
log(GDPpc) * 1990s			-0.032
			[0.203]
log(GDPpc) * 2000s			-0.592***
			[0.168]
log(GDPpc) * 2007s			-0.690***
			[0.167]
Year FE	Y	Y	Y
Observations	863	863	863

Notes: This table reports absolute convergence regressions. The independent variable is the average annualized GDP growth for the subsequent decade, in PPP (from the Penn World Tables v10.0), and the sample contains the data for the first year of each decade since 1960, with 2007 replacing 2010. We exclude countries with population $< 200{,}000$, and for whom rents from natural resources account for $> 75\%$ of GDP. Specification (1) pools the data since 1960. Specification (2) includes a time trend for the absolute convergence β. Specification (3) estimates the absolute convergence β by decade. Year fixed effects are included in all three specifications. Standard errors, clustered at the country-level, are reported in the parentheses. * $p < 0.05$, **$p < 0.01$, *** $p < 0.001$

Balanced panel Since the number of countries in the dataset is growing over time, the above results could reflect the inclusion of the new countries over time, rather than global trends. To investigate this, we show, by decade, what convergence looks like from that decade until present day, among the balanced panel of countries whose data is available from the start of that decade. So, for example, for the 1970s, we plot the 10-year average convergence coefficient, from 1970 to present, for the set of countries who are in the dataset since 1970.

Figure C.3 displays the results of these investigations which hold the set of countries fixed over time. It shows that the change in convergence has little to do with the expansion of the set of countries over the time period - results are remarkably robust to different balanced panels, showing that the original results do indeed reflect a trend towards convergence since 1990.

While the trend towards convergence began around the time of the dissolution of the Soviet Union, the repercussions of which may have been an important driver of the change in convergence, the robustness of the trend to countries which existed before 1990 shows that the change was not mechanical from the addition of the former Soviet countries.

Averaging period Many of the original convergence studies used a fixed baseline year, considering how convergence in income per capita changed when varying the endline year. We argue that to consider trends in convergence itself, rather than use a fixed baseline year, it is better to consider convergence over a fixed interval of time, and how it changes when varying the baseline year. This raises a natural question of what the fixed interval of time should be and whether that interval matters. In the main results, we used a 10-year interval, considering 10 years a good trade-off between allowing us to see medium-frequency trends, without overloading the trend with annual noise. Figure C.4 shows how the convergence coefficient varies when using 1-, 2-, 5- and 10-year averages. 10-year averages show the clearest trend towards convergence. Once we get to 1-year averages, the year-to-year variation dominates, and the trend which is apparent in 5- and 10- year averages is much less apparent.

Measure of income Figure C.5 shows that our finding of a trend towards convergence is not specific to looking at income per capita (as opposed to per worker), nor to using income per capita in Purchasing Power Parity (PPP) adjusted terms from the Penn World Tables v10.0. Namely, we find a broadly similar pattern using income per worker instead of income per capita, using different measures of income from the PWT, and using the World Development Indicators data with income measured in constant 2010 US dollars. Indeed, in the later, the trend is more apparent, and seems to start from 1960, again with a decade of regression in the 1980s.

Specification Figure C.6 shows that our results are however sensitive to the regression specification. Using country fixed effect or country and time fixed effects, instead of time fixed effects as in our baseline specification, we find robust convergence since 1990. However, in part due to the econometric difficulties of using country fixed effects, summarized in Durlauf et al. (2005), we prefer to use cross-country variation as in our baseline specification.

3.2.3 Which countries have driven the change?

To provide more details on the trend to absolute convergence, and to take a first step towards understanding its causes, we consider which countries have driven the change. We do so simply by showing how the trend in convergence changes when removing different groups of countries.

Faster growth of poor countries or slowing-down of rich country growth? Two very different and popular narratives could each lead to the observed trend to convergence: stagnation of the frontier – a drop in the growth rate of richer countries; or faster catch-up growth – a rise in the growth rate of poorer countries.

Figure 5 shows average 10-year growth rate by income quartile, where income quartile is recalculated each year. The richest quartile of countries had the highest growth rate of all quartiles in the 1980s and then switched position entirely to have the lowest growth rate since 2000. The shift was driven both by a slow-down of growth at the frontier - the richest quartile of countries experienced flat growth in the 1990s and then a growth slowdown since 2000 – and faster catch-up growth - the other three quartiles experienced a substantial acceleration in growth in the 1990s. Removing one quartile at a time from our standard test for convergence, Figure C.7, it does appear that in the last decade the trend towards convergence is driven by the richest quartile versus the other quartiles, and that the poorest quartile has if anything been a drag on the trend towards convergence within the other quartiles.

Fewer growth disasters or more growth miracles? Figure C.9 presents the trend in coefficients from Equation 3.2.1 when excluding countries which experienced disasters or growth miracles. The trend towards convergence remains robust, whether we drop episodes of especially low or episodes of especially high growth. Interestingly, the reversion in the 1980s disappears when excluding countries which had a negative 10-year growth rate.

Which regions are driving the change? Figure C.8 presents the trend in coefficients from Equation 3.2.1 when excluding countries from different regions. Again the trend remains robust, although the trend towards convergence in the last twenty years becomes stronger upon excluding Sub-Saharan Africa.

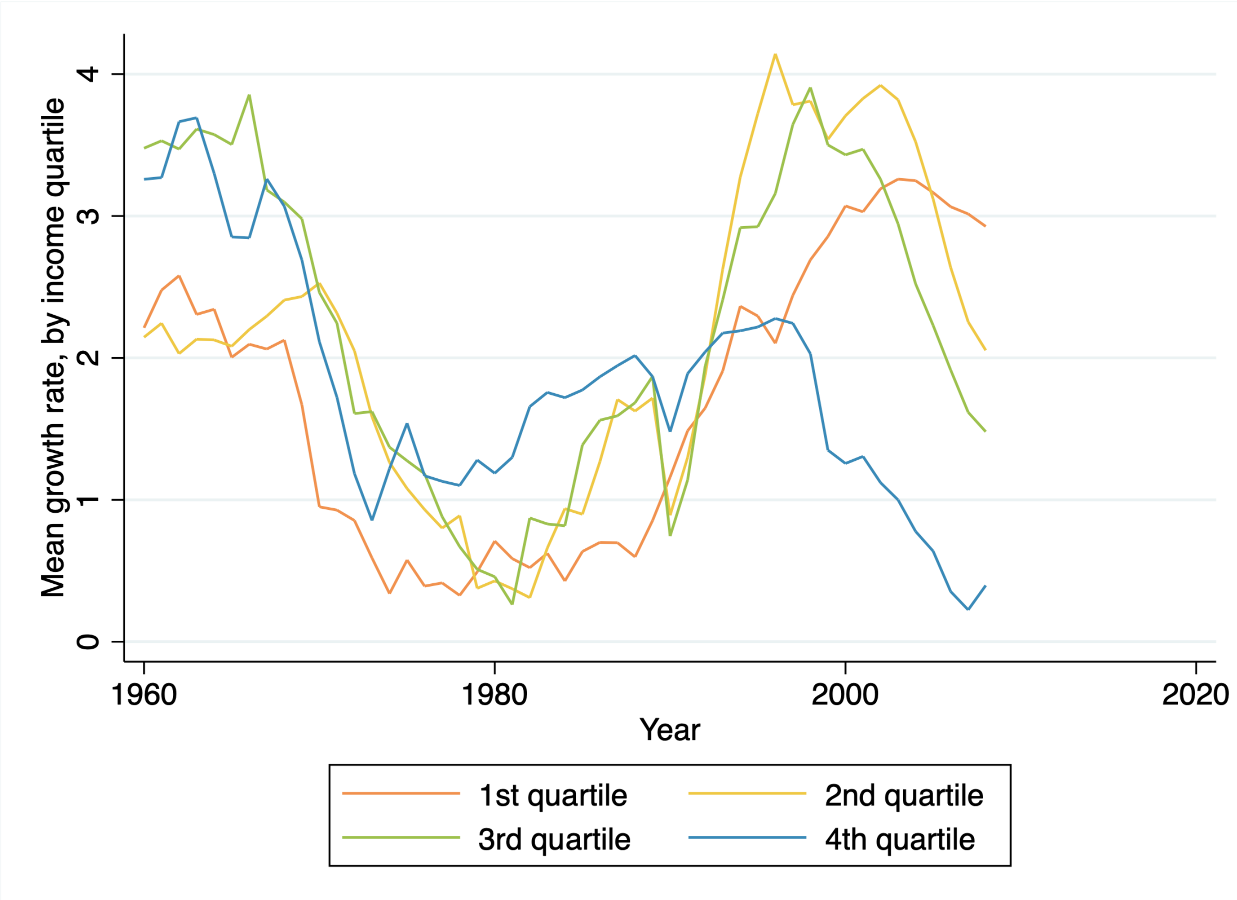
3.2.4 Club convergence

Convergence has been documented among OECD countries (or rich countries) as a group of relatively homogeneous countries (Barro and Sala-i Martin 1992), as evidence for club convergence – convergence among groups of countries which have similar institutions and culture. We revisit this result and show convergence among the rich countries has slowed and shifted towards the general global convergence pattern.

Figure C.11 plots the convergence coefficients in the country sub-sample with income above the Xth percentile.[109] Three decades from 1965 to 1995 yield a similar pattern - strong convergence among high-income countries (above the 60 percentile) while overall there was little absolute convergence. This pattern has changed in the period from 1995 to 2005, and in the most recent decade, convergence holds across all

[109] $X = 0$ corresponds to absolute convergence. X stops by 80, corresponding to the top 20% high-income countries. The sample size would be too small to obtain stable β if X rises above 80.

Figure 5: Trend in income growth by income quartile, 1960-2007



Notes: The plots show the average annual growth in GDP per capita, PPP, for the subsequent decade, averaged by income quartile. Income quartile is classified based on GDP per capita in that year, with the 1st quartile being the lowest income and the fourth the highest.

countries, while convergence among the top 40% of countries by income has stopped.

3.3 Convergence in correlates of income and growth

We next consider global trends in factors that might be determinants of growth - policies, institutions, human capital, and culture - using the same empirical approach as above. While much recent literature emphasizes the persistence of institutions over time (Acemoglu et al. 2001; Michalopoulos and Papaioannou 2013; Dell 2010), we find substantial change and convergence. Overall, 17 out of the 32 Solow fundamentals and short-run correlates for which we have temporal variation exhibit β-convergence from 1985 to 2015, and the correlates have generally converged in the direction of those of more advanced economies, towards what we term development-favored institutions. Moreover, culture has also convergence, with 8 out of 10 measures of culture we consider displaying β-convergence in the World Value Surveys data.

3.3.1 Policies, institutions, measures of human capital, and cultural traits considered

We divide such potential correlates of income and growth into four groups: *enhanced Solow fundamentals* – investment rate, population growth rate, and human capital –variables which are fundamental determinants of steady state income in the enhanced Solow model (Mankiw et al. 1992); *short-run correlates*, other policy and institution variables considered by the 1990's growth literature which may vary at relatively high frequency; *long-run correlates*, institutions and their historical determinants which do not change or which only change slowly, which have been the focus of the recent institutions literature, and geographic correlates of growth; and *culture*.

To tie our hands, we started from a list of variables commonly used in growth regressions, from the Handbook of Economic Growth chapter on "Growth econometrics" (Durlauf et al. 2005), constraining ourselves to those variables which covered at least 40 countries from 1996. We then added to this list numerous cultural variables and historical determinants of institutions which have played a central role in the empirical growth literature since Durlauf et al. (2005). While we obviously cannot consider convergence for historical or geographic variables – they are included for the empirical exercises in the next section – we are able to study convergence of a number of cultural variables, albeit with a smaller country sample than for the policy and institutional variables.

Table 12 summarizes the data sources and sample period of the resulting correlates. There are 5 enhanced Solow fundamentals and 27 short-run correlates divided into four broad categories: political institutions, governance, fiscal policy, financial institutions. Not all of these short-term correlates are comparable over time, for example the World Governance Indicators and Heritage Freedom Scores are standardized each year. We obviously cannot study convergence nor average changes for such variables, but we include them in the table as we do use them for our conditional convergence comparison, in Section 3.4 of the paper. For certain figures in the paper, we pick one representative variable from each category, displayed in **bold** in the table: Polity 2 score, the WGI rule of law, government spending (% GDP), credit provided by the financial sector (% GDP). Equivalent figures with the other variables can be found in the Appendix.

Table 12: List of policies, institutions, and human capital variables

Category	Variable	Data Source	Data Period
Enhanced Solow Fundamentals	**Gross capital formation (% GDP)**	WDI	1960-2017
	Population growth rate	WDI	1960-2017
	Barro-Lee Years of Education Age 25-29	Barro-Lee Data	1950-2010
	Education Gap (Male-Female)	Barro-Lee Data	1950-2010
	Labor Force Participation Rate	WDI	1960-2017
Political Institution	**Polity 2 Score**	Polity IV Project	1960-2018
	Freedom House Political Rights	Freedom House	1973-2018
	Freedom House Civil Liberty	Freedom House	1973-2018
	Media Freedom Score	Freedom House	1979-2018
	WGI Political Stability	WGI	1996-2018
Governance Quality	**WGI Rule of Law**	WGI	1996-2018
	WGI Government Effectiveness	WGI	1996-2018
	WGI Regulatory Quality	WGI	1996-2018
	WGI Control of Corruption	WGI	1996-2018
	Overall economic freedom index	Heritage Freedom	1995-2019
	Government Integrity	Heritage Freedom	1995-2019
	Business Freedom	Heritage Freedom	1995-2019
	Investment Freedom	Heritage Freedom	1995-2019
	Property Rights	Heritage Freedom	1995-2019
Fiscal Policy	Taxes on income & cap. gains (% of revenue)	WDI	1972-2017
	Taxes on goods and services (% of revenue)	WDI	1972-2017
	Tax Burden Score	Heritage Freedom	1995-2019
	Equal-weighted Tariff	WDI	1988-2017
	Value-weighted Tariff	WDI	1988-2017
	Private Investment (% Total Investment)	IMF	1960-2015
	Government Spending (% GDP)	WDI	1960-2017
	Military Expenditure (%GDP)	WDI	1960-2017
Financial Institution	Inflation	WDI	1960-2017
	Central Bank Independence (Weighted)	Garriga (2019)	1970-2012
	Credit by financial sector	WDI	1960-2017

Table 13: Change and convergence in policies, institutions, and human capital, from 1985* to 2015*

	Dev-Favored	1985 Mean	2015 Mean	Change (in σ_{1985})	t-stat	Convergence β
Gross capital formation (% of GDP)	High	22.07	24.18	0.23	1.88	-2.98***
Population growth (annual %)	Low	1.99	1.42	-0.43	-6.36	-1.53***
Barro-Lee Education Age 20-60	High	6.19	8.80	0.86	27.64	-0.16
Education Gap (Male-Female)	Low	0.97	0.33	-0.66	-9.57	-0.81***
Labor Force Participation Rate	Low	62.48	62.61	0.01	0.27	-0.66***
Polity 2 Score	High	-0.87	4.69	0.73	9.40	-2.03***
Freedom House Political Rights	High	5.86	6.53	0.30	4.16	-1.39***
Freedom House Civil Liberty	High	5.72	6.56	0.41	6.28	-1.36***
Media Freedom Score	High	52.63	49.93	-0.12	-2.32	-0.88***
WGI Political Stability	High	-	-	-	-	-
WGI Government Effective	High	-	-	-	-	-
WGI Regulatory Quality	High	-	-	-	-	-
WGI Rule of Law	High	-	-	-	-	-
WGI Control of Corruption	High	-	-	-	-	-
Overall Economic Freedom Index	High	-	-	-	-	-
Government Integrity	High	-	-	-	-	-
Property Rights	High	-	-	-	-	-
Business Freedom	High	-	-	-	-	-
Equal-weighted Tariff	Low	9.46	4.36	-0.47	-3.79	-3.46***
Value-weighted Tariff	Low	8.11	3.09	-0.70	-5.71	-3.38***
Taxes on Income & Capital Gain	High	25.54	28.79	0.20	1.94	-1.61***
Taxes on Goods and Services	N/A	28.47	31.38	0.21	1.39	-2.51***
Government Spending (%GDP)	High	15.90	15.96	0.01	0.12	-1.61***
Tax Burden Score	N/A	-	-	-	-	-
Private Investment	High	0.63	0.63	0.00	-0.01	-1.60***
Military Expenditure (%GDP)	N/A	3.38	1.89	-0.47	-6.70	-2.10***
Inflation	N/A	16.19	2.25	-0.54	-6.33	-3.07***
Central Bank Independence	N/A	0.38	0.60	1.77	10.92	-2.56***
Credit to Private Sector	High	31.46	55.60	0.95	7.34	0.89**
Credit by Financial Sector	High	49.42	69.15	0.47	3.87	-0.98
Financial Freedom	High	-	-	-	-	-
Investment Freedom	High	-	-	-	-	-

Notes: This table presents the average correlate in 1985 (or the earliest available year, denoted 1985*) and 2015 (or the latest available year, denoted 2015*), and convergence rate over the three decades. Column (2) reports the development-favored correlates determined by their correlation with GDP per capita in 1985. "N/A" refers to the potential correlates which are not significantly correlated with income in our base year 1985, i.e. where δ_{1985} is insignificant. Columns (3) and (4) report the raw mean of correlates in 1985* and 2015* respectively. Columns (5) and (6) report the change in the correlates between 1985* and 2015*, normalized by the standard deviation in 1985* and corresponding t-statistics. Column (7) is the correlate convergence β, obtained by regressing the decade-average correlate change from 1985* to 2015* on the correlate in 1985*.

To help interpret the direction of change of correlates, Table 13 Column (3) shows which correlates were "development-favored" in 1985 (or the earliest available year), defined by their correlation with log GDP in 1985. Correlates are defined as high (or low) development-favored if the coefficient from regressing the correlate on log GDP is positive (or negative), with statistical significance at a 10% level. A high-income country tends to have a higher Polity 2 score, higher rule of law score, higher government spending (as a % of GDP), more financial credit, and higher education attainment. Five correlates cannot be signed: taxes on goods and services, tax burden score, military expenditure, inflation, and central bank independence.

We use five variables to measure political institutions: the Polity 2 score from the Center of Systematic Peace (1960-2018), the Freedom House political rights score (1973-2018), the Freedom House civil liberty score (1973-2015), the Press Freedom score (1979-2018),[110] and the political stability score (1996-2018) from Worldwide Governance Indicators (WGI).

Governance variables - distinct from political institutions - measure whether the public system functions well. We use four variables (1996-2018) from the WGI Project: government effectiveness, regulatory quality, the rule of law, control of corruption; and five variables (1995-2019) from the Index of Economic Freedom by the Heritage Foundation: Overall economic freedom index, government integrity, business freedom, investment freedom, and property rights. The sample size of countries in the Economic Freedom database rises from 97 in 1995 to 145 in 2005, and then 159 in 2015. Variables under the governance and political institutions categories are all positively correlated with economic development.

The fiscal policy category mainly captures the following three dimensions: taxation, tariffs, and government interventions / expenditures. Taxation measurements include taxes on income and capital gains (percentage of total tax revenue), taxes on goods and services (percentage of total tax revenue), and a tax burden score. Equal-weighted and value-weighted tariffs are measures of the policy-induced barriers to trade. A state with strong government interventions and expenditures tends to have a lower private investment (% total investment), more government spending (% spending), and higher military expenditure. In general, high-income countries are more likely to adopt free trade and low government intervention, but there is not clear pattern in our data on taxation.

The financial institutions category includes six variables: a central bank independence index constructed

[110]The press freedom score ranges from 0 to 100. A high score represents less press freedom in the original data. We transform the data as 100 minus the original data so that high score translates into more press freedom

by Garriga 2016; inflation, credit to the private sector (% GDP), and credit provided by the financial sector (% GDP), all from the WDI; and financial freedom and investment freedom scores from the Index of Economic Freedom. Higher financial development is positively associated with economic development, while central bank independence (CBI) and inflation are ambiguous by our approach. The high inflation of 1990 was not constrained to developing countries, but a global issue. Central bank independence adoption rose over time and inflation was brought under control (Rogoff 1985; Alesina and Gatti 1995; Fischer 1995; Alesina and Summers 1993; Grilli et al. 1991; Alesina 1988).

The labor category includes Barro-Lee average educational attainment of the age groups 20-60 (Barro and Lee 2013), gender inequality in education (male minus female in educational attainment), and labor force participation rate. High-income countries are more educated and have less gender inequality and lower labor force participation.

The following sections examine changes in correlates from 1985 to 2015 and their rate of convergence, β_{Inst}, estimated from the following equation:[111] [112]

$$\Delta_{1985 \longrightarrow 2015} Inst_i = \beta_{Inst} Inst_{i,1985} + \alpha + \epsilon_i$$

The country sample is time-varying (mostly increasing) as datasets add new countries into the sample.

Before presenting results for individual correlates, we test the convergence of all of our correlates jointly in table C.4, which presents the joint significance of each category using seemingly unrelated regressions. All variables are available since 1996. Thus we report results for 1996-2006 in Panel A and 2006-2016 in Panel B.[113] For both decades, we confidently reject (p-value $< 10^{-14}$) the hypothesis that convergence in correlates does not exist.

[111] If data were not available in 1985, we use the earliest available year for the analysis. For example, the rule of law score from WGI start in 1996. Table 13 Column (4) reports the 1996 average and the baseline year for the correlate convergence β_{Inst} in Column (7) is 1996 as well.

[112] In the Appendix, we also plot the standard deviations of the correlate metrics as the σ-convergence for correlates (Figures C.15 - C.19).

[113] The joint significance holds for any decade in 1996-2017.

3.3.2 Enhanced Solow fundamentals

Human capital Human capital is a robust predictor of income growth, as emphasized in the seminal literature Lucas Jr (1988), Barro (1991), Mankiw et al. (1992), Sala-I-Martin (1997), Barro and Lee (1994).[114] Education augments labor productivity (Lucas Jr (1988)), facilitates technological progress (Romer (1990)), and industrializes economy (Squicciarini and Voigtländer (2015)).[115]

We measure time-varying human capital with the Barro-Lee average schooling years of population age 20-60. Figure C.12 Panel C reports the beta convergence. The convergence in human capital starts from 1975. Since 1975, poor countries start to gain faster growth in educational attainment and gradually catch up with rich countries. In addition, education levels in some well-educated populations have stagnated, and the data implies that 13 average years of education appears to be a soft cap for many countries.[116] We also observe a meaningful shrinkage in education attainment inequality across gender. The education advantage of male is expected to decline by 8.1% per decade.

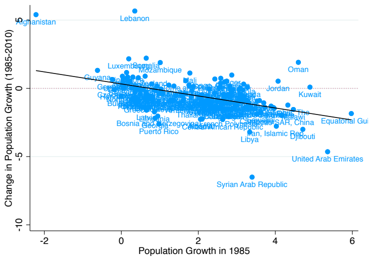
Investment Investment is development-favored — according to our definition — and we observe a moderate growth from 22.07% in 1985 to 24.18% in 2015, which translates to 0.23 standard deviations in 1985. Figure C.12 Panel B suggests that convergence is initially concentrated and then witnesses a decrease, with the coefficient fluctuating around -6 and slowly moving towards -4 after 2000. Figure 6 Panel B exhibits a strong mean-reversion: with one percent higher investment in 1985 corresponds to a negative growth of 2.98% per decade. With most countries slowly decreasing their investment, certain developing countries like Mozambique, Ethiopia, and Angola, increased investment.

Population growth There has been a sizeable and statistically significant beta-convergence in population growth, with a prediction of -1.53 in growth each decade. Population growth is not development-favored and we observe a decrease in growth from 1.99% in 1985 to 1.42% in 2015, translating to -0.43 standard deviations in 1985. Figure C.12 Panel A reports the beta convergence which fluctuates between -4 and -2

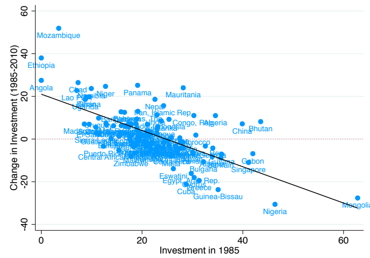
[114] Government cannot directly manage human capital, but many policies can significantly influence educational attainment, such as budgetary decisions, school-building campaigns, curriculum, and minimum school leaving age.

[115] See Krueger and Lindahl (2001) for extensive reviews on micro and macro empirical evidence on schooling and growth.

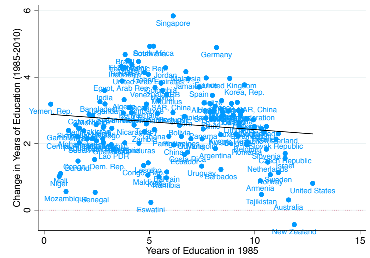
[116] In 2010, only nine countries — Switzerland, Denmark, United Kingdom, Iceland, Japan, South Korea, Poland, Singapore, United States — have population with more than 13 years of education. South Korea and Singapore are the only two nations pushed the number above 14.



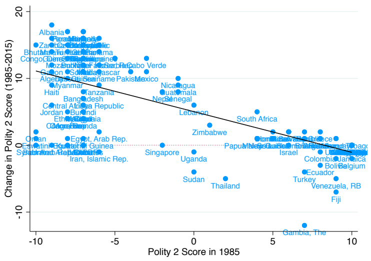
A: Population Growth



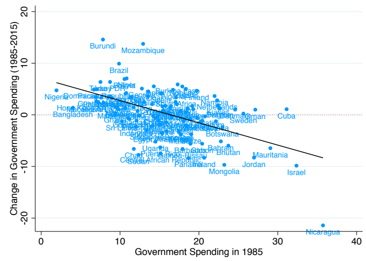
B: Investment



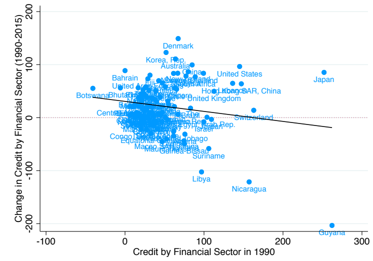
C: Barro-Lee Years of Education



D: Polity 2



E: Government Spending



F: Credit

Figure 6: Convergence in correlates: level in 1985 versus change 1985-2015

Notes: This figure plots the correlate change from 1985 (or the earliest available year) to 2015 against the baseline correlate level. We include eight correlates: Population growth rate (%), Investment rate (% of GDP), Barro-Lee average years of education among 20-60 year olds, Polity 2 score, rule of law score, property rights score, government spending (% of GDP), credit by financial sector. The sample for each figure is the full set of countries for which the relevant data is available in both 1985 and 2015.

before 2000, after which we witness a sharp decline towards -6. After 2000, population growth has fallen for poor, while population growth has stagnated for some of the rich countries. Figure 6 Panel A reports that most countries in our sample witnessed a negative growth in population.

3.3.3 Short-run correlates

Political Institutions Political institutions exhibit pervasive beta convergence and sigma convergence, with particularly strong convergence in the 1990s. We use the polity 2 score form the Polity IV project as our primary democracy measure, which ranges from -10 to 10. -10 represents dictatorship and 10 represents perfect democracy. Figure C.14 shows that the average polity 2 score hits its low point in 1978, at below -2, then the score gradually climbed back to zero in 1990. Then, the average democracy score jumped up to 2 after the dissolution of the Soviet Union, and persistently improved to above 4 in the next 25 years.

Figure C.15 shows the plot of coefficients for beta-convergence in political institutions. Polity 2 score, political rights, and civil liberty yield similar results, including in the coefficient magnitude. The long-run average of coefficients is around -0.2. The deep institutional reforms in the 1990s lead the coefficients to drop below -0.3 in that decade and then gradually move back the historical average -0.2. The beta institutional convergence is statistically significant in any single year's cross-sectional regression. Beta-convergence in media freedom and political stability also holds since 1995 and the convergence pattern is very stable in the recent two decades.

Panel B reports the standard derivation of the five political institutions. The sigma convergence of democracy started in 1990. The standard deviation of polity 2 score fluctuates around 7.5 before 1990, sharply declines to 6.5 in 2000, and persistently decreases to 6 in 2015. The four other variables show a similar pattern: the standard deviation after 2000 is lower than that prior to 1990.

The broad adoption of democracy is a central aspect of the convergence of political institutions. Figure 6 plots the change in the democracy score from 1990 to 2010 against the democracy score in the baseline year 1990. The spread of democracy is a global phenomenon, not just constrained to Soviet Union countries. Many countries with Polity 2 score below 5 radically shift their political institutions towards democracy.

Meanwhile, movements away from democracy are also common. Table C.2 summarizes the proportion of countries with increases and downgrades in democracy scores. After 1980, still, roughly 10% of countries experienced falls in democracy in each decade. If we focus, somewhat arbitrarily, on countries with a Polity 2 score reduction of at least three in a decade, then most democracy degeneration events happen in countries with positive democracy scores — 6 out of 8 in the 1980s, 5 out of 5 in the 1990s, 7 out of 7 in the 2000s, 4 out of 5 in 2010-2015.

Developing countries are much more likely to experience political reforms, both towards democracy and against democracy, while rich countries successfully maintain their democratic politics. Table C.3 shows logit regressions of increases or decreases in Polity 2 score on income level for the six decades. Panel A reveals that low-income countries are only more likely to gain democracy in the 1960s and 1990s, but not much in other periods. However, in Panel B, low-income countries are also more exposed to democracy setbacks, except in the 1990s.

Fiscal Policy Despite a lack of consensus on optimal fiscal policy, global average government spending has stayed close to 16% of GDP throughout 1985 to 2015. Moreover, there has been sizeable and statistically significant beta convergence in government spending: one percent higher spending in 1990 predicts a subsequent relative -1.61% decline. Figure 6 Panel E exhibits strong mean-reversion: one percent higher in government spending in 1996 predicts 1.61 percent reduction in the next two decades, where a high t-stat of 9.6 and the R-squared is as high as 41%.

This pattern is not unique to government spending, but common for all fiscal policy variables. The convergence β ranges from -3.46 (Equal-Weighted Tariff) to -1.60 (Private Investment), significant at the 1% level.

A large empirical literature argues that lower policy-induced barriers to trade are associated with faster economic growth (Frankel and Romer 1999). We document a significant trade liberalization from 1990 to 2010 — equal-weighted tariff drops from 9.46% to 4.36%; similarly value-weighted tariff drops from 8.11% to 3.09% — more than 50% tariff cut on average. Beta-convergence coefficient fluctuates around -6 but gradually moves to -4 in the recent decades. The magnitude is notably large compared with other correlates. The convergence is large in both equal-weighted and value-weighted tariff data. Figure C.17 Panels B4 indicates that the variance of tariffs sharply reduces in 1995, and that trade liberalization expands internationally. The standard deviation of tariffs stays below 5 after 2010.

Financial Institutions We see mixed evidence regarding financial credit convergence: modest convergence happens when countries are equal-weighted, while there is also substantial credit growth in a few large highly-leveraged developed economies.[117] Credit is development-favored, according to our definition, and we do observe substantial credit expansion from 49.4% of GDP in 1990 to 69.15% of GDP in 2010, which translates into 0.47 standard deviations in 1990. One percent higher credit in 1990 corresponding to a -0.98% decrease per decade. However, the convergence pattern is less persistent over time — Figure C.12 Panel F shows the convergence is particularly concentrated in the 1980s and 1990s.

Figure 6 Panel F implies that convergence happens in both directions. Under-leveraged economies, such as Denmark, Australia, and South Korea, expanded their financial sector. At the same time, many countries de-leveraged: out of 123 countries in our sample, 40 reduced the amount of credit. Highly-leveraged economies were more likely to contract credit, potentially to manage the risk of recessions. In total, twelve countries hold credit-to-GDP ratio above 100% in 1990, reduced credit by 23% on average after two decades.[118] At

[117] There is almost surely divergence if we weight countries by their credit market size. Credit growth is highly concentrated in countries with low interest rates and in reserve currencies, e.g., US dollars, Euro, and Japanese Yen.

[118] Three developed economies - US, UK, and Japan - are notable exceptions: highly leveraged economies continue to expand bank credit even more. Japanese credit was over 200% of GDP in 1990, and the interest rate dropped below 1% in 1996. The US and UK were both highly leveraged, over 100% relative to GDP,

the other extreme, seventeen countries with credit below 15% of GDP expand the credit by 21% till 2010.

Financial stability also increased significantly. For example, episodes of high inflation became much less frequent. Figure C.18 Panels A1 and B1 report the convergence pattern for inflation. We don't find robust convergence until 1980, when episodes of very high inflation were still widespread. The beta-convergence coefficients stay negative with a narrow confidence interval since 1980. Sigma convergence happens since 1990: the standard deviation runs from the peak above 30 to the trough below 5 in 2010. Modern monetary policy reduced the occurrence of hyper-inflation and contributed to the convergence in inflation. Figure C.13 plots the proportion of countries which experience a) inflation above 200%, b) inflation above 100%, c) inflation above 50%, d) inflation above 15% in a specific year. All the four lines start to decline since 1995. From 1972 to 1995, about 35% of countries had annual inflation above 15%. and 10% countries experienced inflation over 100%. After 2000, almost no country has inflation above 50% while less than 10% countries bears inflation above 15%.

3.3.4 Culture

Culture and values can also evolve. We use the World Value Survey to measure trust, perceptions on inequality, views on political matters (respect for authority, interest in politics, joining in boycotts), and the importance of family, work, politics, religion, and traditions. To best match the time horizon considered for other correlates, we pick countries which are surveyed in both Wave 6 (2010-2014) and at least one of Waves 3-5 (1995-2009). 49 countries remain in our sample.[119]

Each cultural variable is the population-weighted average based on the whole sample.[120]. To adjust for the different survey frequency, we take the annualized cultural change (between the first survey year in Waves 3-5 and the survey year in Wave 6) and regress it on the baseline year's culture.

Beta-convergence holds for eight out of ten cultural variables in Table C.1. People in different countries reach a broader consensus on politics, inequality, work ethics, and the importance of family and traditions. We find no convergence in the trust level and the importance of religion.

and continued to increase another approximate 100%. Similarly, both countries lowered interest rates near zero after the 2008 financial crisis and the 2020 Covid-19 induced recession. The unprecedented low-interest rates further fueled outstanding credit.

[119] 33 countries are available both in Waves 3 and 6.

[120] Appendix provides the survey question list for each cultural variable

3.4 Linking converging income with convergence of its correlates

In this section, we revisit the cross-sectional relationships between income and growth and their correlates, detailing how the relationships have changed and linking these changes to the emergence of absolute convergence in the past two decades. First, we consider the relationship between income levels and the potential correlates of income and growth. Then, we turn to the relationship between income growth and the correlates - growth regressions. Finally, combining the two, we turn to the question of conditional convergence - the prediction of neoclassical growth models - and a simple decomposition of the gap between unconditional and conditional convergence.

3.4.1 Simple empirical framework

For our simple empirical investigation of the link between income, correlates, and growth, we consider two basic cross-country regressions. First, the cross-country relationship between income and institutions:

$$Inst_{i,t} = \nu_t + \delta_t log(GDP_{i,t}) + \epsilon_{i,t} \tag{17}$$

where δ_t is the slope of the relationship and ν_t is the institutional level in year t.

Second, the relationship between institutions and growth, controlling for income - the classic growth regression:

$$\Delta_t log(GDP_{i,t}) = \alpha_t + \beta_t^* log(GDP_{i,t}) + \lambda_t Inst_{i,t} + \epsilon_{i,t} \tag{18}$$

where $Inst_{i,t}$ can be an individual institution or a set of institutions, λ_t is the growth regression coefficient(s) of the institution(s), when controlling for baseline income, and β_t^* is the conditional convergence coefficient, controlling for the institution(s).

In this framework, when conditioning on a single correlate, the standard omitted variable bias formula allows us to decompose the difference between absolute convergence (β) and conditional convergence (β^*) as the product of the coefficient of the income-institution regression, δ_t, and the growth regression coefficient, λ_t:

$$\beta_t - \beta_t^* = \delta_t \times \lambda_t$$

Data availability varies substantially across different correlates, making it difficult to construct a balanced panel with many correlates. This has two implications for our analysis. First, we largely focus on univariate versions of the growth regression, equation 18, including one correlate at a time. This misses the effect of changes in the relationships across correlates, so we also run several multivariate analyses trading off the number of correlates with the size of the panel. Second, in the main analysis we focus on the time period 1985-2015, since that is the period over which the majority of our correlate variables are available for a large number of countries. We also present certain results for the period 1960-1985 for those correlates for which we have the data to do so.

3.4.2 Correlate-Income relationship across countries

Prosperity is correlated with the rule of law, democracy, fiscal capacity, education, among others. We have shown above that income has started to convergence and that correlates have converged substantially. Are these changes related? Did countries simply shift along the lines in the cross-country relationship between income and correlates, or did the lines themselves change?

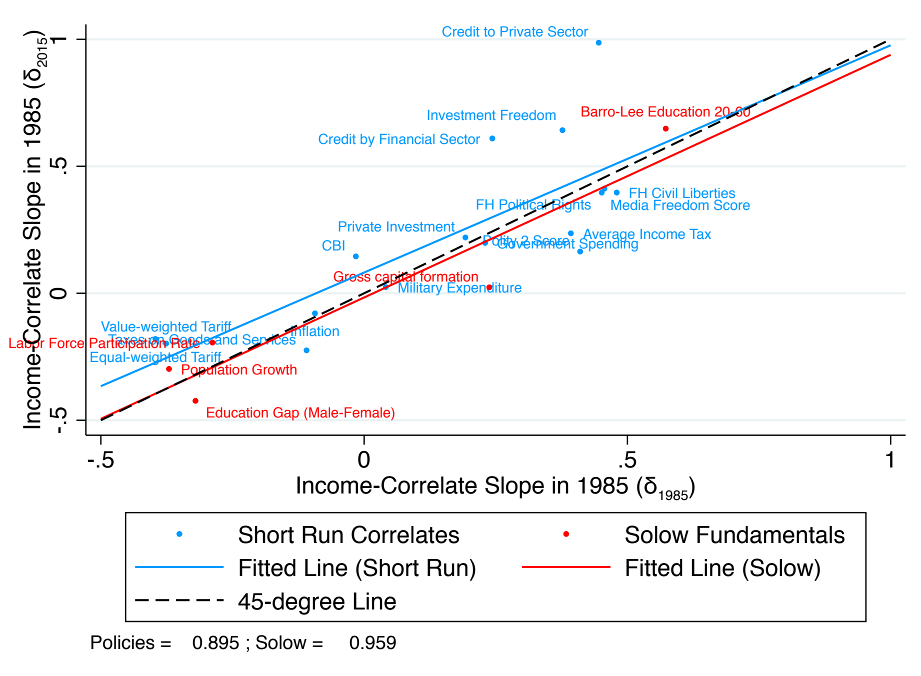
Figure C.20 investigates this, plotting whether changes in correlates are as would be expected from changes in income, given the baseline cross-country relationship between the two. Overall, we see that actual changes are on average in line with those predicted from income growth: the fitted line is approximately on the 45-degree line. This suggests that overall, levels of correlates *conditional on income* have remained constant.

However, for individual correlates, the actual changes are generally quite far from those predicted by baseline relationships. Education and financial development have improved by much more than predicted by income growth. Education has increased, and the gender gap in education became significantly smaller. Many "best practices" of financial institutions have been broadly pursued as well: well-managed inflation, central bank independence, credit expansion as a crucial part of the economic stimulus package, lower tariffs to embrace globalization. Political institutions improved almost as much as predicted. Meanwhile, measures of governance stagnated or even declined: property rights protection, investment freedom, business freedom, and political stability experienced sizable decline from 1985 to 2015.

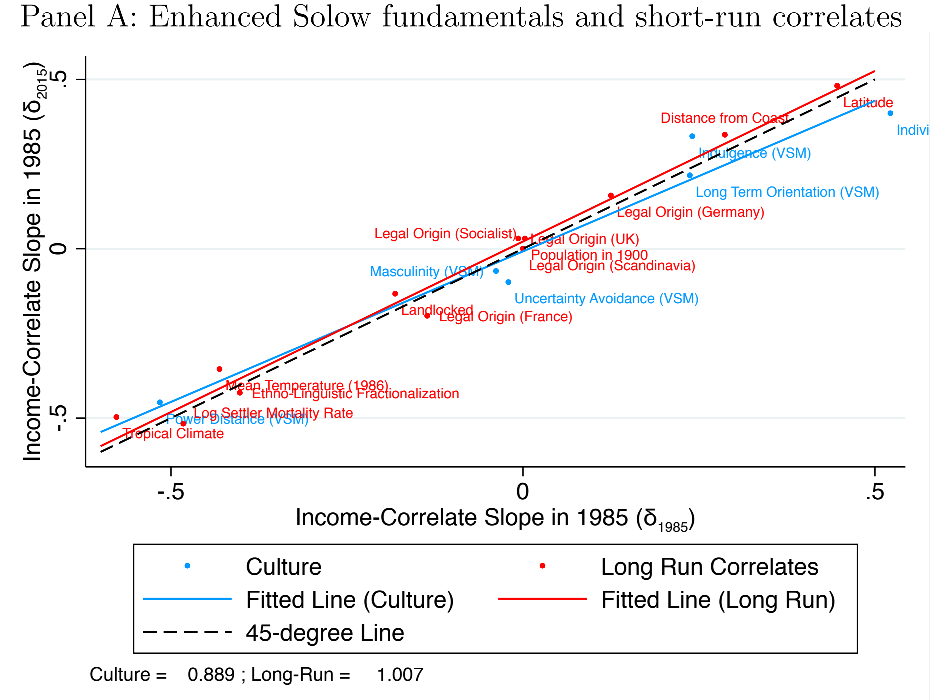
We have seen that on average correlates have changed as predicted by their cross-country relationship with income, but what has happened to these cross-country relationships themselves? Figure 7, which normalizes correlates by their in 1985[121], shows the slopes of these correlate-income regressions, the δ_ts in

[121] In Figure **??**, we normalize standard deviations of correlates in 1985 and 2015, respectively. The fitted line coincides with the 45-degree line, and the R-squared is as high as 92%.

Equation (17) , changed remarkably little. The slopes in 1985 is sufficient to explain the 69% of variation in slopes three decades later. The explanatory power (R-squared) rises to 87.5% if three outliers (financial credit, credit to private sector, and tertiary education) are excluded. The other 30 correlates scatter precisely along the 45-degree line. The results are also reported in Table 14.



Panel A: Enhanced Solow fundamentals and short-run correlates



Panel B: Long-run correlates and culture

Figure 7: Correlate-income slopes, 1985 vs. 2005

Notes: This figure plots the coefficients from regressing the normalized correlates on the log(GDP) in 1985 and 2015. The solid line is the fitted line of the scatter plot. The dashed line refers to the 45-degree line as a benchmark.

$$\frac{Inst_{i,t}}{SD(Inst_{1985})} = \delta_t log(GDPpc)_{i,t} + \nu_t + \epsilon_{t,i}$$

Table 14: Correlate-income and growth-correlate relationships

	δ_{1985}	δ_{2005}	λ_{1985}	λ_{2005}	$\delta\lambda_{1985}$	$\delta\lambda_{2005}$	N
Gross capital formation (% of GDP)	0.263***	0.111 *	0.277	0.385*	0.073	0.043	115
Population growth (annual %)	-0.354***	-0.187***	-0.676***	-0.653***	0.239	0.122	136
Barro-Lee Education Age 20-60	0.593***	0.619***	1.019***	0.579*	0.604	0.359	118
Education Gap (Male-Female)	-0.326***	-0.447***	-0.560 **	-0.151	0.183	0.067	118
Labor Force Participation Rate	-0.314***	-0.270***	-0.411	0.357*	0.129	-0.096	160
Polity 2 Score	0.409***	0.185***	0.905***	0.326	0.370	0.060	124
Freedom House Political Rights	0.451***	0.331***	1.103***	0.152	0.498	0.050	132
Freedom House Civil Liberty	0.480***	0.334***	0.970***	0.132	0.466	0.044	132
Media Freedom Score	0.466***	0.444***	0.079	-0.034	0.037	-0.015	152
WGI Political Stability	-	-	-	-	0.061	0.023	159
WGI Government Effective	-	-	-	-	-0.092	0.141	158
WGI Regulatory Quality	-	-	-	-	-0.222	-0.025	159
WGI Rule of Law	-	-	-	-	-0.145	0.010	159
WGI Control of Corruption	-	-	-	-	-0.141	-0.092	159
Overall Economic Freedom Index	-	-	-	-	-0.264	-0.179	97
Government Integrity	-	-	-	-	-0.153	-0.145	97
Property Rights	-	-	-	-	-0.117	-0.186	97
Business Freedom	-	-	-	-	-0.030	-0.156	97
Equal-weighted Tariff	-0.611***	-0.225***	0.567	1.066	-0.346	-0.240	45
Value-weighted Tariff	-0.571***	-0.246***	0.437	-0.406	-0.249	0.100	45
Taxes on Income & Capital Gain	0.394***	0.286 **	-0.036	0.092	-0.014	0.026	48
Taxes on Goods and Services	-0.169	-0.123	-0.602 *	0.253	0.102	-0.031	49
Government Spending (%GDP)	0.248***	0.230***	-0.174	-0.259	-0.043	-0.060	111
Tax Burden Score	-	-	-	-	0.005	-0.004	97
Private Investment	0.204***	0.218***	0.049	0.179	0.010	0.039	133
Military Expenditure (%GDP)	0.112	0.048	0.054	-0.536	0.006	-0.026	110
Inflation	-0.096	-0.048 **	-0.114	-1.177**	0.011	0.056	124
Central Bank Independence	-0.029	0.323***	-0.607 **	0.005	0.018	0.002	100
Credit to Private Sector	0.459***	0.937***	0.740 **	0.161	0.340	0.151	104
Credit by Financial Sector	0.251***	0.572***	0.373	0.139	0.093	0.079	104
Financial Freedom	-	-	-	-	-0.066	-0.077	97

Investment Freedom	-	-	-	-	0.133	0.007	97
Population in 1900	-0.218 *	-0.125	0.476	0.507**	-0.104	-0.063	58
Power Distance	-0.534***	-0.497***	-0.065	0.775***	0.034	-0.385	60
Individualism	0.545***	0.460***	-0.562 *	-0.691***	-0.306	-0.318	60
Masculinity	-0.034	-0.053	-0.250	-0.136	0.008	0.007	60
Uncertainty Avoidance	-0.024	-0.095	-0.493 *	-0.098	0.012	0.009	60
Indulgence	0.246***	0.294***	0.824***	0.452**	0.203	0.133	69
Long Term Orientation	0.230 **	0.210 **	-0.029	-0.434**	-0.007	-0.091	70
Legal Origin (UK)	-0.007	0.026	0.555***	0.041	-0.004	0.001	136
Legal Origin (France)	-0.136 **	-0.171***	-0.621***	-0.282	0.084	0.048	136
Legal Origin (Germany)	0.125 **	0.131 **	0.197	0.470**	0.025	0.061	136
Legal Origin (Scandinavia)	0.237***	0.219***	-0.051	-0.077	-0.012	-0.017	136
Legal Origin (Socialist)	-0.130 *	-0.080	0.002	0.352**	-0.000	-0.028	136
Log Settler Mortality Rate	-0.570***	-0.563***	-0.814 **	-0.333	0.464	0.188	84
Mean Temperature (1986)	-0.547***	-0.475***	-0.001	0.489**	0.000	-0.233	60
Distance from Coast	0.287 **	0.329***	0.832 **	0.072	0.239	0.024	61
Ethno-Linguistic Fractionalization	-0.405***	-0.417***	-0.601 **	0.050	0.244	-0.021	124
Landlocked	-0.182***	-0.136 **	0.286	0.189	-0.052	-0.026	129
Latitude	0.469***	0.477***	0.696 **	0.063	0.326	0.030	129
Tropical Climate	-0.578***	-0.509***	-0.064	0.768***	0.037	-0.391	89

This table reports the coefficients of the cross-sectional regressions of correlates on income and of (ten year average) growth on correlates, in 1985* to 2005*. In particular, the coefficients δ and λ are estimated from the following regressions:

$$\Delta log(GDPpc)_{i,t} = \beta_t log(GDPpc)_{i,t} + \lambda_t \frac{Inst_{i,t}}{SD(Inst_{1985})} + \alpha_t + \epsilon_{i,t}$$

$$\frac{Inst_{i,t}}{SD(Inst_{1985})} = \delta_t log(GDPpc)_{i,t} + \nu_t + \epsilon_{i,t}$$

Columns (2) and (3) report the cross-section relationship δ estimated estimated in 1985* and 2005*. Columns (4) and (5) report regressions of income growth in the next decade on correlates, controlling for income at the start of the decade, in 1985*-1995 and 2005*-2015. Columns (6) and (7) report the difference between absolute converge and conditional convergence constructed using the standard omitted variable bias formula by constructing the product $\lambda\delta$. Column (8) reports the number of observations in the specifications, respectively. The sample only includes countries with non-missing correlate variables in 1985. Missing entries correspond to correlates which are standardized each year: the standardization makes comparisons over time of λ and δ difficult to interpret, but are cancelled out in for product $\lambda\delta$.

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

3.4.3 Correlate-Growth relationship in growth regressions

Growth regression coefficients, the λ_ts in Equation (18), reduced somewhat in magnitude over time for human capital and other Solow fundamentals (the investment rate and the population growth rate), but they were correlated. Education, for example, strongly predicts higher economic growth at a roughly similar magnitude in decades 1985-1995 and 2005-2015. A one s.d. increase in educational attainment predicts 1.02% annualized GDP growth in 1985-1995, and the number falls to 0.58% for 2005-2015. Countries in which female have more equal access to education resources have grown faster: a one s.d. reduction in gender gap (in schooling years) predicts 0.56% higher GDP growth in 1985-1995, and 0.15% in 2005-2015.

In contrast, coefficients on short-run correlates reduced more substantially from 1985-2005, with essentially zero correlation between the two periods. Table 14 Columns (4) and (5) report λ_{1985} and λ_{2005}.[122] Figure 8 plots λ_{2005} re-estimated with the same country sample[123] two decades later 2005-2015. The slope of the correlate-growth relationships have shrunk towards zero and the slope of fitted line in Figure 8 is only 0.270.

Long-run correlates and culture fall in between Solow fundamentals and short-run correlates in the persistence of their correlation with growth. Figure 8 Panel B shows that the slope of the long-run correlate-growth relationship has shrunk towards zero with 0.228 as the slope of the fitted line. However, the correlate-growth relationship is more stable for culture with 0.635 as the slope of the fitted line.

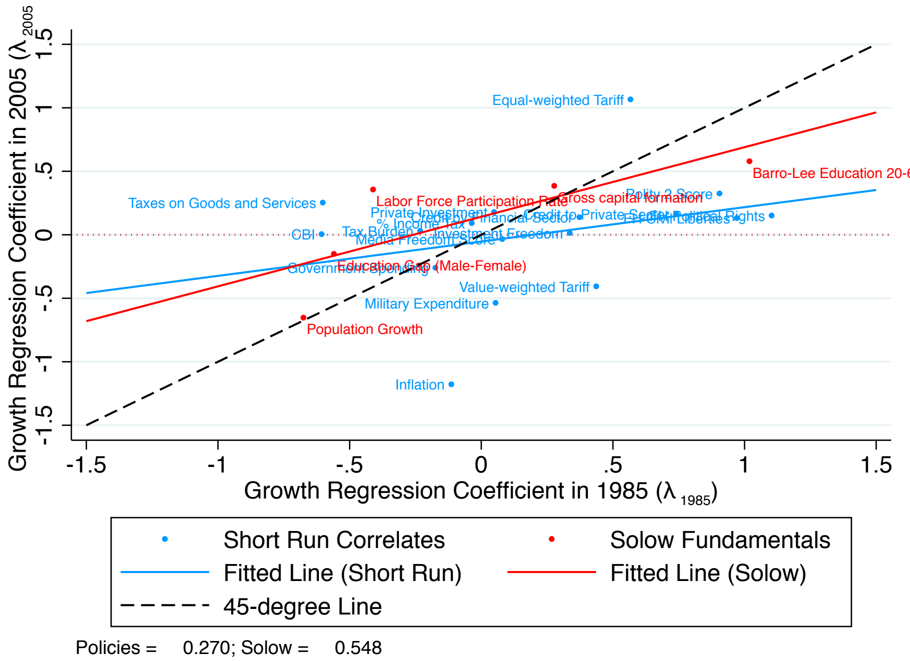
3.4.4 Shrinking gap between conditional and unconditional convergence

One response to the failure of unconditional convergence was to move to the idea of conditional convergence: convergence conditional upon possible determinants of steady-state income, such as policies and institutions (Barro and Sala-i Martin 1992). Conditional convergence has been widely supported in the data (Durlauf et al. 2005).

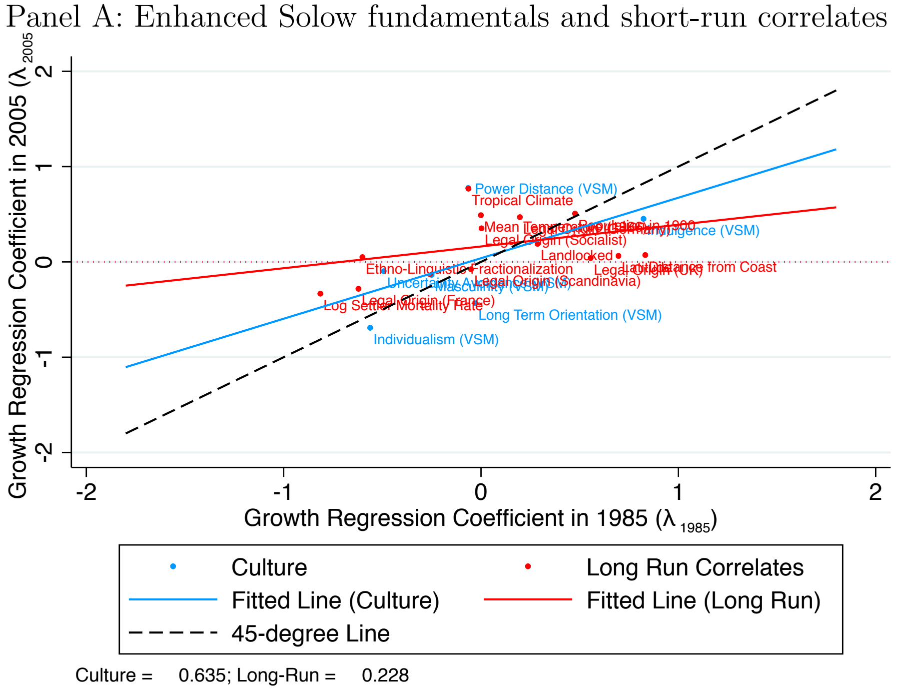
This leads to the natural question of whether the shift towards unconditional convergence represents a reduction of the importance of conditioning – a shrinking of the gap between conditional and unconditional convergence. Or has conditional convergence itself become faster?

[122] Our time horizon shrinks to 1985-2005 to accommodate the growth regression. Table 14 Columns (2) and (3) report δ_{1985} and δ_{2005}, instead of δ_{2015} discussed in Section 4.2.

[123] The country sample is selected with valid GDP and correlates data in the starting year. The sample size typically decreases slightly from 1985 to 2005 since some countries vanish in the two decades.



Panel A: Enhanced Solow fundamentals and short-run correlates



Panel B: Long-run correlates and culture

Figure 8: Growth-correlate slopes, 1985 vs. 2005

Notes: This figure plots the λ_{1985} and λ_{2005}, the 10-year growth regression coefficients in 1985 and 2005, corresponding to Table 14.

$$100\frac{log(GDPpc)_{i,t+10} - log(GDPpc)_{i,t}}{10} = \beta_t log(GDPpc)_{i,t} + \lambda_t \frac{Inst_{i,t}}{SD(Inst_{1985})} + \alpha_t + \epsilon_{i,t}$$

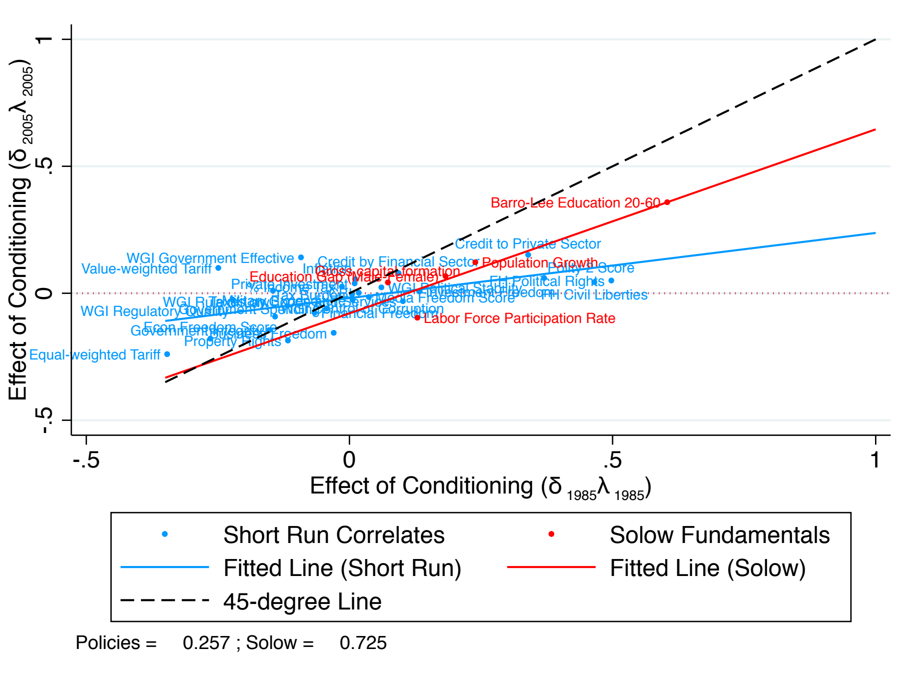
λ_{1985} and λ_{1985} is estimated using a balanced panel, for each correlate. The fitted lines are regressions of λ_{2005} on λ_{1985} for the different sets of correlates.

Univariate When conditioning on a single correlate, according to the omitted variable bias formula, the gap between unconditional and conditional convergence can be written as the product of the correlate-income slope δ and the growth-correlate slope λ. Figure 9 and Table 14 report the changes in this gap from 1985-2005. Correlate-by-correlate, qualitatively the trend in the effect of conditioning is similar to that of the growth regression coefficients: Solow fundamentals have the most stable effect, long-run correlates and culture are intermediate, and short-run institutions have the least stable effect. However, what is harder to see from this Figure, but can be seen clearly in C.23, is that the effect on conditioning has on average shrunk to around zero for short-run and long-run correlates since 1980, while for Solow fundamentals it has remained more steady. The same figure also shows that the effect of conditioning on correlates increased substantially between 1960 and 1980, although for a much smaller set of countries and correlates.

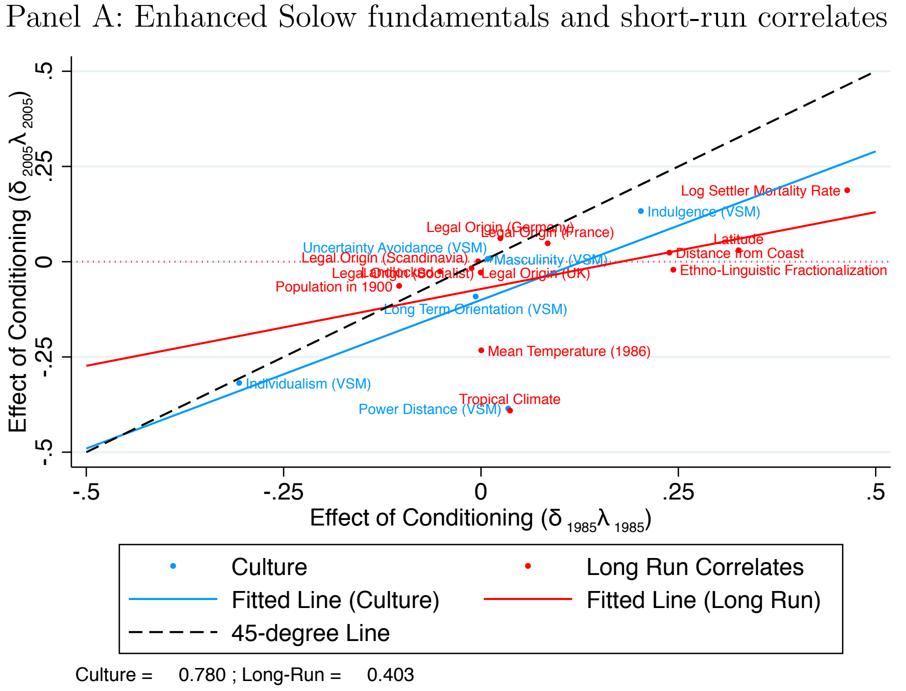
Multivariate Many of the classic conditional convergence regressions control for a large set of policies and institutions. In attempting to run such multivariate regressions, there is a harsh trade-off in constructing the country-year sample, between the number of observations and the number of available correlates, which is why we consider the univariate results our main results in this section. However, to attempt to run a multivariate version, we (somewhat arbitrarily) selected a sample of 72 countries and include the following institutional variables: polity 2 score, Freedom House political rights, Freedom House civil liberty, private investment ratio, government spending, inflation, credit provided to the private sector, credit by the financial sector, Barro-Lee educational attainment, and gender gap in schooling years.

Figure 10 plots both the conditional and unconditional convergence coefficients, from 1985 to 2007. We see that, while the unconditional convergence coefficient has trended down, there has been no clear trend in the conditional convergence coefficient, and the gap between the two has closed substantially. Thus, in terms of what has driven the change in unconditional convergence, it is not that conditional convergence has gotten faster, but instead, that unconditional convergence has become closer to conditional convergence.

Table 16 reports the coefficients for growth in three decades from 1985 to 2015. From 1985 to 1995, correlates explain substantial variation in economic growth and convert absolute divergence to conditional convergence. The ten correlates jointly take down the coefficient from 0.33 (t=1.37) to -0.627 (t=-1.15). In 2005-2015, the unconditional economic growth rate is -0.75% (t=-4.79). Correlates still effectively cut the convergence rate to -1.15% (t=-3.77), however, no sign indicates conditional convergence is faster than two decades ago.



Panel A: Enhanced Solow fundamentals and short-run correlates



Panel B: Long-run correlates and culture

Figure 9: Gap between unconditional and conditional convergence (univariate), 1985 vs. 2005

Notes: This figure plots the $\delta_{1985}\lambda_{1985}$ and $\delta_{2005}\lambda_{2005}$, with Panel A plotting policies and proximate institutions and Solow fundamentals, and Panel B plotting culture and long-run institutions. $\delta_{1985}\lambda_{1985}$ and $\delta_{2005}\lambda_{2005}$ are estimated from the following regressions with the GDP growth in sample periods 1985*-1995* and 2005*-2015*, linking conditional and unconditional convergence using a univariate approach.

$$\beta_t = \tilde{\beta}_t + \delta_t \lambda_t$$

The fitted line is a regression of λ_{2005} on λ_{1985} just for the set of policies and proximate institutions.

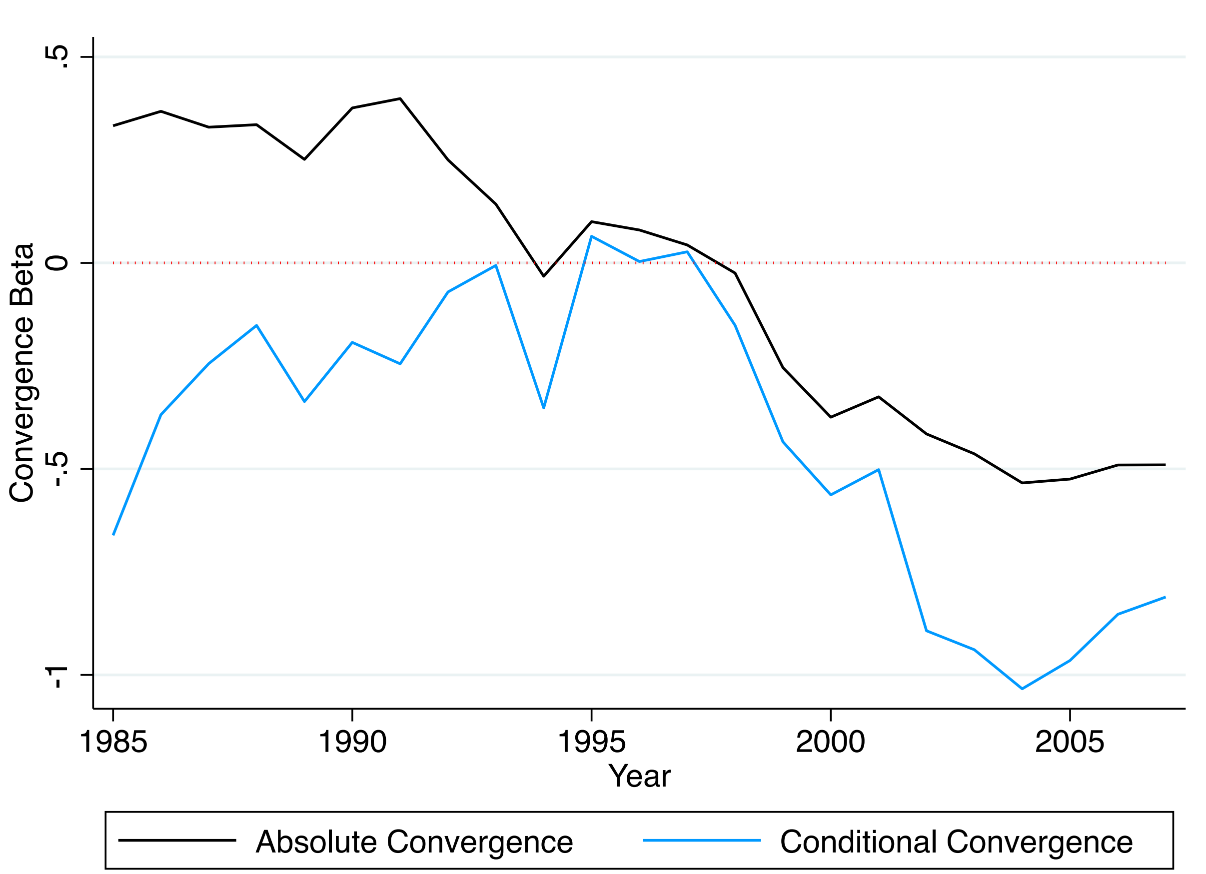


Figure 10: Absolute convergence converging to conditional convergence (multivariate)

Notes: The country sample contains 72 countries with sufficient institutional variables in 1985. The solid line represents the absolute convergence β-coefficient and the dashed line represents the conditional convergence β-coefficient. The institutional co-variates include polity2 score, Freedom House political rights, Freedom House civil liberty, private investment ratio, government spending, inflation, credit provided to private sector, credit by financial sector, Barro-Lee education attainment, and education gender gap. Minor imputations apply: missing values in institutions are imputed with the latest available data point. The red dotted line is the benchmark of no convergence.

Table 15: Absolute and conditional convergence in 1985 and 2005

	Annual growth in GDPpc 1985-1995				Annual growth in GDPpc 2005-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP PC	0.333	-0.485	-0.260	-0.627	-0.748***	-1.177***	-0.743***	-1.146***
	(0.240)	(0.537)	(0.435)	(0.547)	(0.156)	(0.289)	(0.243)	(0.305)
Investment		0.363		-0.00976		0.388		0.438
		(0.397)		(0.480)		(0.305)		(0.280)
Population growth		-1.035		-1.095*		-0.428***		-0.412***
		(0.627)		(0.657)		(0.131)		(0.147)
Barro-Lee Education 20-60		0.480		0.434		0.456		0.609**
		(0.443)		(0.593)		(0.349)		(0.306)
Polity 2 Score			-0.609	-1.070			0.705*	0.0151
			(0.694)	(0.704)			(0.393)	(0.395)
FH Political Rights			1.284	1.573*			-0.288	0.269
			(0.970)	(0.922)			(0.458)	(0.412)
Private Investment			-0.199	-0.276			0.304	0.267
			(0.326)	(0.329)			(0.406)	(0.356)
Government Spending			-0.0593	0.0595			-0.569**	-0.798***
			(0.384)	(0.417)			(0.276)	(0.252)
Inflation			-0.0925	-0.00337			-1.705**	-1.671**
			(0.232)	(0.240)			(0.836)	(0.830)
FH Civil Liberties			0.0825	-0.427			-0.0493	-0.274
			(0.683)	(0.759)			(0.782)	(0.710)
Credit to Private Sector			0.800*	0.730			0.403	0.386
			(0.471)	(0.546)			(0.294)	(0.270)
Credit by Financial Sector			-0.323	-0.439			-0.651*	-0.679**
			(0.510)	(0.592)			(0.348)	(0.334)
Constant	-1.462	5.677	0.0559	5.180	9.007***	11.19***	10.56***	12.15***
	(2.168)	(4.645)	(3.269)	(4.266)	(1.489)	(2.050)	(2.220)	(2.379)
Observations	73	73	73	73	113	113	113	113
R-Squared	0.0227	0.160	0.148	0.226	0.201	0.326	0.302	0.422

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports absolute and conditional convergence regressions, for 1985*-1995 and 2005*-2015, for the fullest list of Solow and short-run correlates which allow a reasonable sample size of 72 in 1985. The covariates include Investment, Population growth, Barro-lee education attainment, polity2 score, Freedom House political rights, Freedom House civil liberty, private investment ratio, government spending, inflation, credit provided to private sector, credit by financial sector, and education gender gap. Columns (1-4) report regressions for 1985-1995, and columns (5-8) for 2005-2015. Column (1) is the absolute convergence regression. Column (2) conditions on the enhanced Solow fundamentals - the fundamental determinants of steady state income in the Solow model. Column (3) conditions on other policies and institutions and column (4) conditions on both. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.5 Conclusion

There has been a trend toward absolute convergence since the late-1980s, resulting in absolute convergence since 2000. This trend towards convergence is consistent with neoclassical growth models and models in which catch-up growth is easier than growth at the frontier, and inconsistent with the set of endogenous growth models which predict divergence. While divergence was the norm over a long period of recent history (Pritchett 1997), the rapid trend to convergence over the last 20 years suggests something important has changed. Breaking down convergence by income quartiles shows both a broad increase in the rate of catch-up growth, the breadth of which does not support a model in which countries catch up only above a certain income threshold, and a growth slowdown at the frontier. What could have driven this change: faster catch-up *conditional* on correlates, due to globalization for example, or the convergence of correlates themselves, with the end of the Cold War and the adoption of the Washington Consensus?

Most correlates of growth and income - policies, institutions, and culture - have converged during the same period, towards those of rich countries. Some of these changes have been gradual, such as changes in government spending and in fertility, consistent with modernization theory (Inglehart and Baker 2000), and *on average* the size of the changes has been as predicted by income growth, under the cross-country correlate-income relationship. However, other changes have happened remarkably quickly, such as the adoption of VATs, or marriage equality, or the spread of democracy after the fall of the Soviet Union, and these more rapid changes may be better explained with theories of contagion or technology adoption (Dobbin et al. 2007). While some aspects of convergence happened independently of external forces, international institutions played a role in other aspects of convergence, for example the IMF and the World Bank encouraged the adoption of the Washington Consensus (Easterly 2019), and the World Health Organization provides technical guidance and best practice for health policy.

As correlates and growth have changed, so have the relationships between them: the coefficients of growth regressions. All types of correlates considered – Solow fundamentals, other short-run correlates, long-run correlate, and culture – have seen their growth coefficients shrink. Most robust are the Solow fundamentals, for which a regression of the coefficients in 2005 on those of 1985 has a coefficient of 0.6. Long-run correlates and culture were somewhat stable, while short-run correlates' coefficients in 2005 bore little relation to their coefficients in 1985.

As a result of this shrinking in growth regression coefficients, the gap between unconditional and conditional convergence has also shrunk substantially. Absolute convergence has converged to conditional convergence, the prediction of neoclassical growth, while the latter has held throughout the period. In the parlance of club convergence, policies and institutions have converged, so that now more countries are "in the convergence club".

What drove these changes since the late 1980s; why was there not also a trend towards convergence in the preceding two decades, when correlates were already converging; and why have growth regression coefficients since shrunk? While faster catch-up conditional on correlates is likely part of the explanation for the trend in convergence, and the shrink in growth regression coefficients may in part be explained by earlier overfitting, we have focused on the convergence of correlates. Our preferred narrative, in terms of parsimony, which is admittedly speculative, is as follows. Measures of policies and institutions are noisy measures of what really matters. Since the fall of the Soviet Union in 1991 and the adoption of the Washington consensus, there has been rapid convergence in policies and institutions. This has happened both for our measures of policies and institutions and for what really matters, and as such any remaining measurable differences in the former may no longer be indicative of the latter.

Do these results give cause for optimism or pessimism regarding whether changes in policies and institutions can lead to catch-up up growth? The persistence literature gives cause for pessimism, if what really matters for steady-state income is deep, persistent determinants, which may be hard to change. However, first we have shown evidence of convergence in culture, suggesting that even persistent determinants may change relatively rapidly. Second, more substantially, our results suggest that malleable policies and institutions did matter for growth in the 1990s, and that when they subsequently (partially) converged there was a shift to income convergence. Yet, malleable policies now seem to matter less, while long-run correlates (and especially Solow fundamentals) have remained important.

Table 16: Absolute and conditional convergence in 1985 and 2005

	Annual growth in GDPpc 1985-1995				Annual growth in GDPpc 2005-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP PC	0.333	-0.485	-0.260	-0.627	-0.748***	-1.177***	-0.743***	-1.146***
	(0.240)	(0.537)	(0.435)	(0.547)	(0.156)	(0.289)	(0.243)	(0.305)
Investment		0.363		-0.00976		0.388		0.438
		(0.397)		(0.480)		(0.305)		(0.280)
Population growth		-1.035		-1.095*		-0.428***		-0.412***
		(0.627)		(0.657)		(0.131)		(0.147)
Barro-Lee Education 20-60		0.480		0.434		0.456		0.609**
		(0.443)		(0.593)		(0.349)		(0.306)
Polity 2 Score			-0.609	-1.070			0.705*	0.0151
			(0.694)	(0.704)			(0.393)	(0.395)
FH Political Rights			1.284	1.573*			-0.288	0.269
			(0.970)	(0.922)			(0.458)	(0.412)
Private Investment			-0.199	-0.276			0.304	0.267
			(0.326)	(0.329)			(0.406)	(0.356)
Government Spending			-0.0593	0.0595			-0.569**	-0.798***
			(0.384)	(0.417)			(0.276)	(0.252)
Inflation			-0.0925	-0.00337			-1.705**	-1.671**
			(0.232)	(0.240)			(0.836)	(0.830)
FH Civil Liberties			0.0825	-0.427			-0.0493	-0.274
			(0.683)	(0.759)			(0.782)	(0.710)
Credit to Private Sector			0.800*	0.730			0.403	0.386
			(0.471)	(0.546)			(0.294)	(0.270)
Credit by Financial Sector			-0.323	-0.439			-0.651*	-0.679**
			(0.510)	(0.592)			(0.348)	(0.334)
Constant	-1.462	5.677	0.0559	5.180	9.007***	11.19***	10.56***	12.15***
	(2.168)	(4.645)	(3.269)	(4.266)	(1.489)	(2.050)	(2.220)	(2.379)
Observations	73	73	73	73	113	113	113	113
R-Squared	0.0227	0.160	0.148	0.226	0.201	0.326	0.302	0.422

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports absolute and conditional convergence regressions, for 1985*-1995 and 2005*-2015, for the fullest list of Solow and short-run correlates which allow a reasonable sample size of 72 in 1985. The covariates include Investment, Population growth, Barro-lee education attainment, polity2 score, Freedom House political rights, Freedom House civil liberty, private investment ratio, government spending, inflation, credit provided to private sector, credit by financial sector, and education gender gap. Columns (1-4) report regressions for 1985-1995, and columns (5-8) for 2005-2015. Column (1) is the absolute convergence regression. Column (2) conditions on the enhanced Solow fundamentals - the fundamental determinants of steady state income in the Solow model. Column (3) conditions on other policies and institutions and column (4) conditions on both. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A Chapter 1 Appendix: Figures and Tables

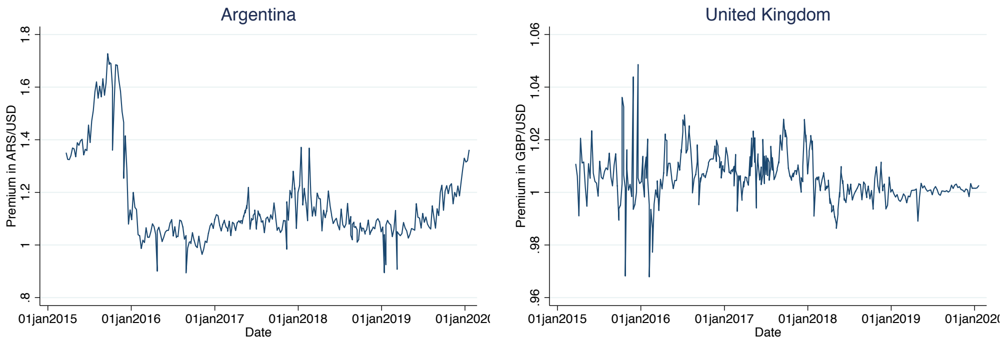


Figure A.1: Price Deviation - Argentina and United Kingdom

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

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

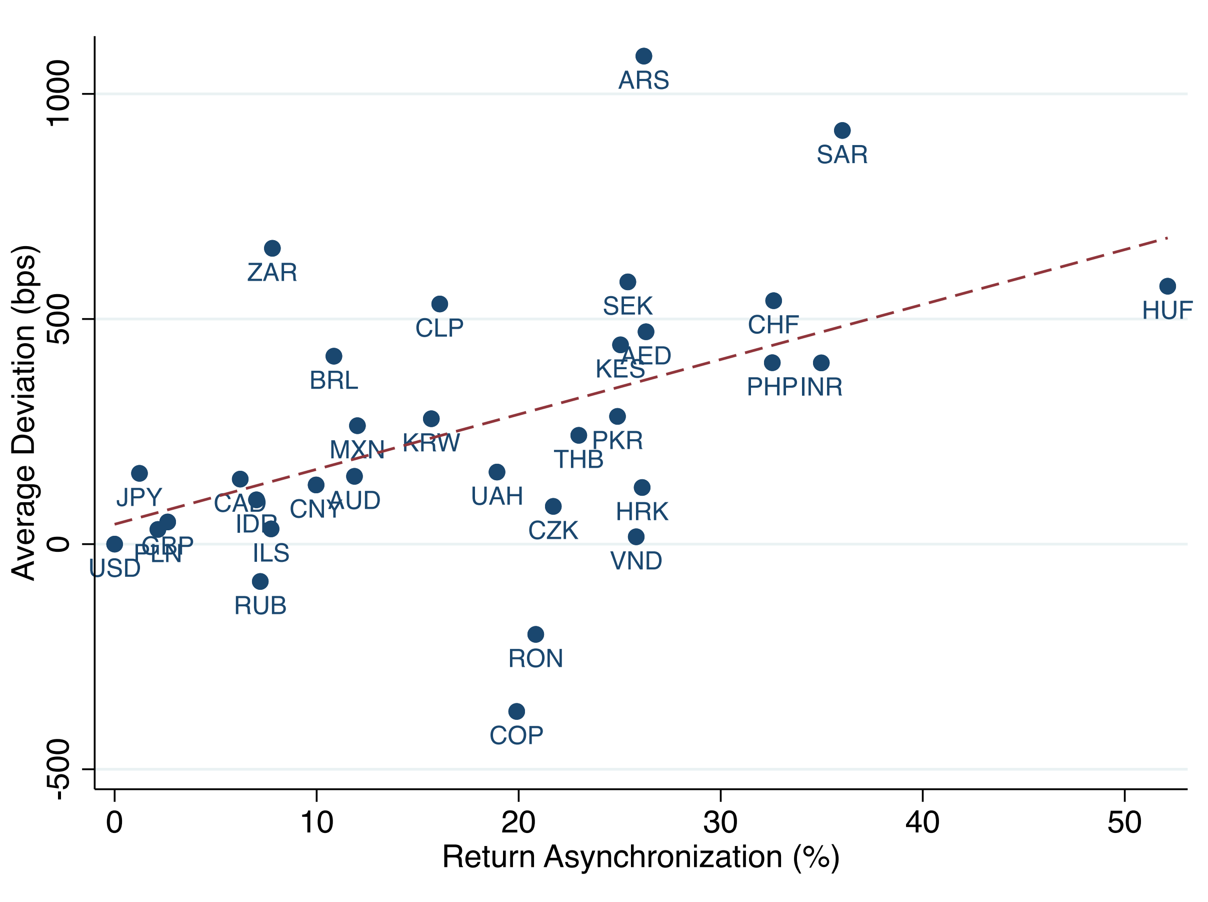


Figure A.2: Return Asynchronization and Average Deviation

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

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

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

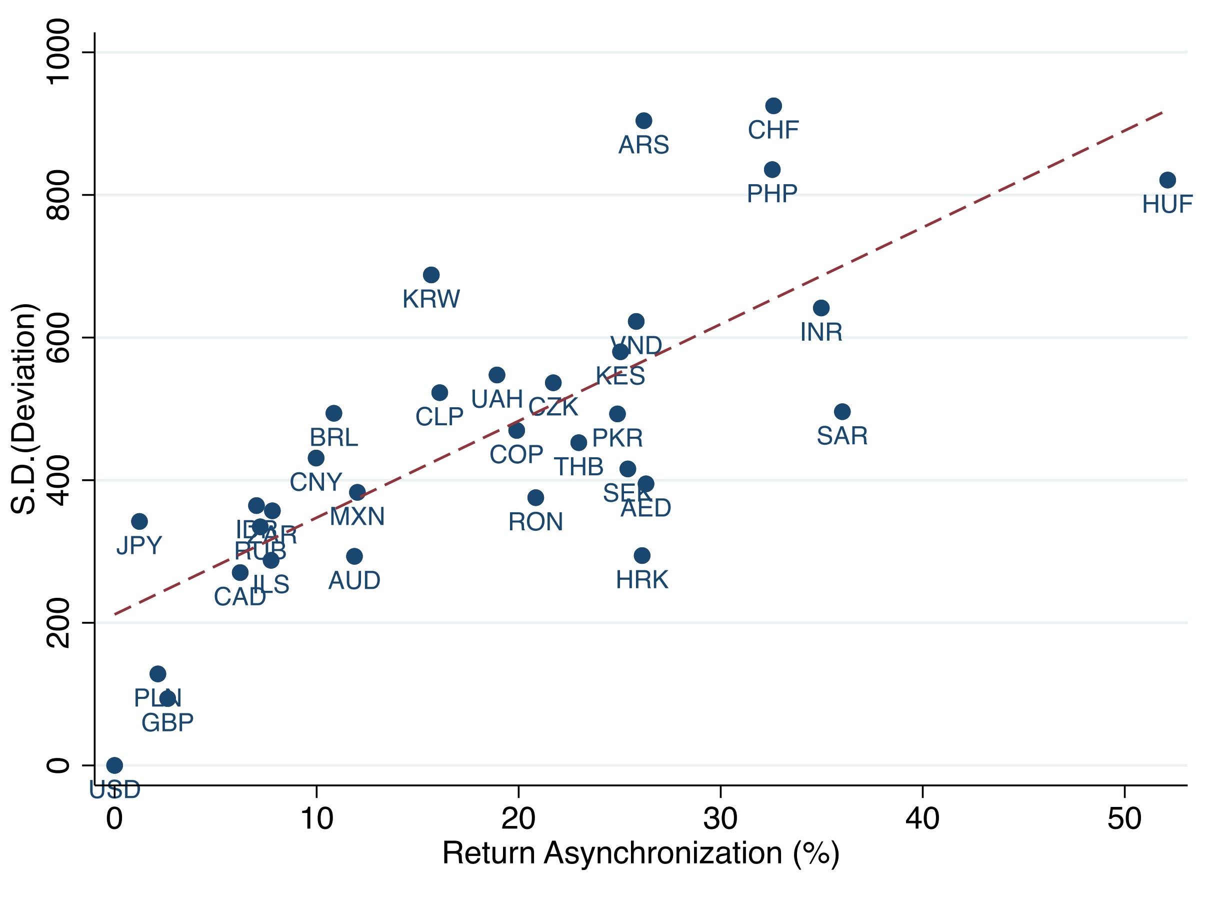


Figure A.3: Return Asynchronization and SD(Deviation)

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

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

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

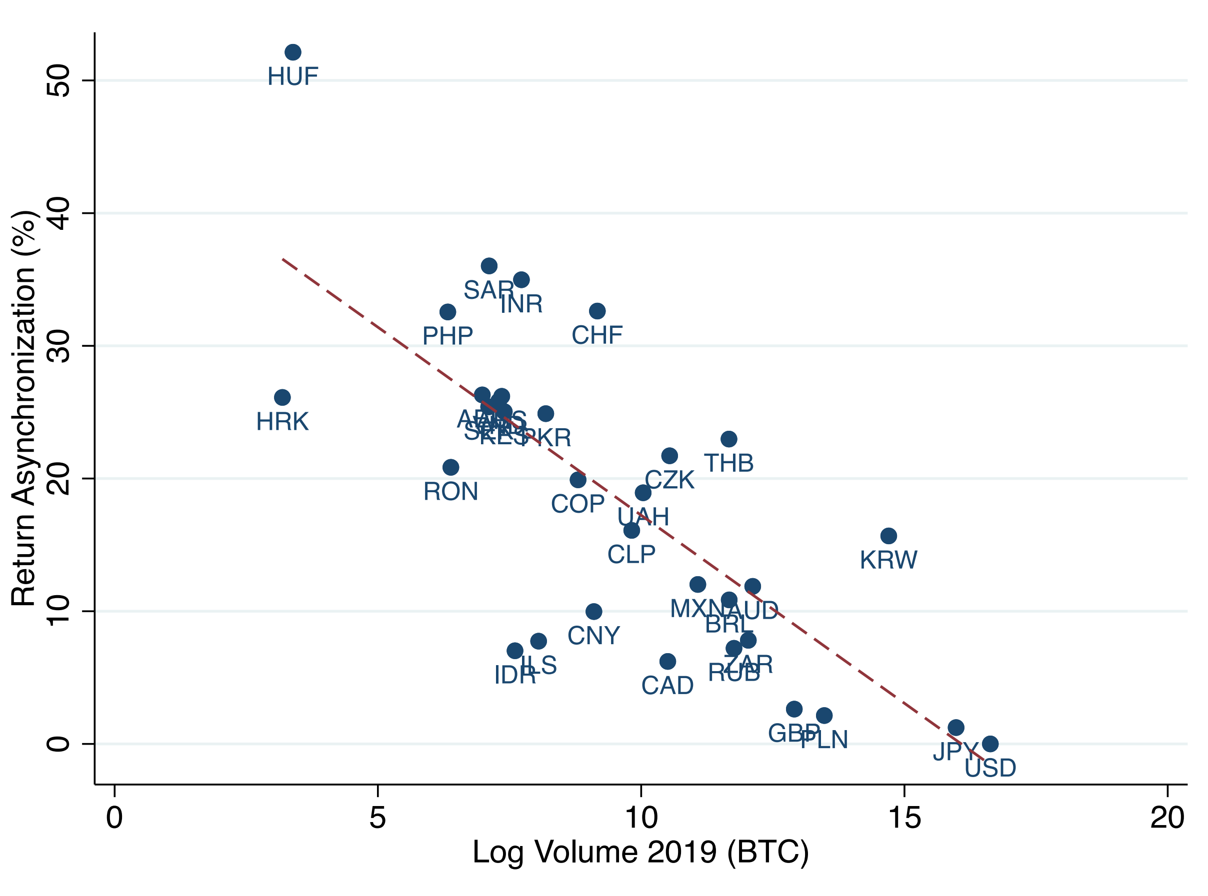


Figure A.4: Return Asynchronization and Liquidity

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

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

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

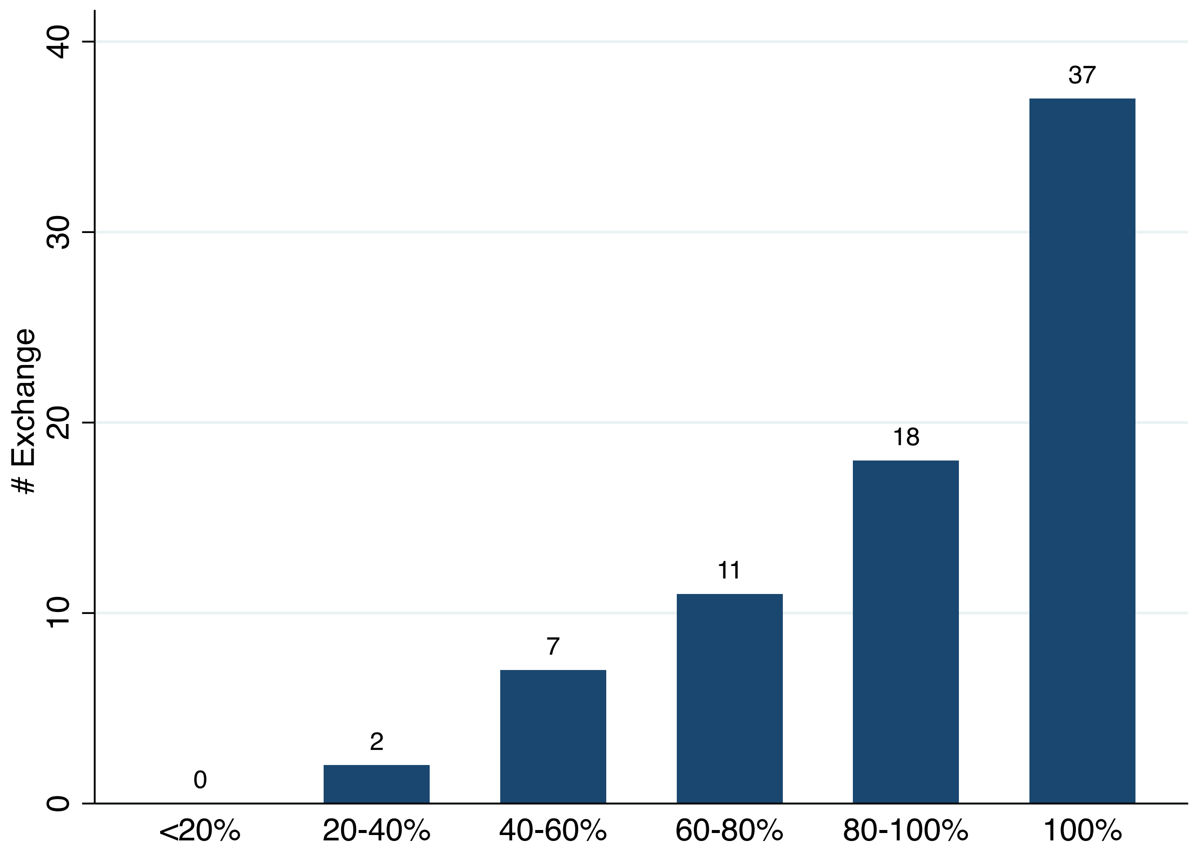


Figure A.5: Exchanges by Volume Share of Primary Trading Pair

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

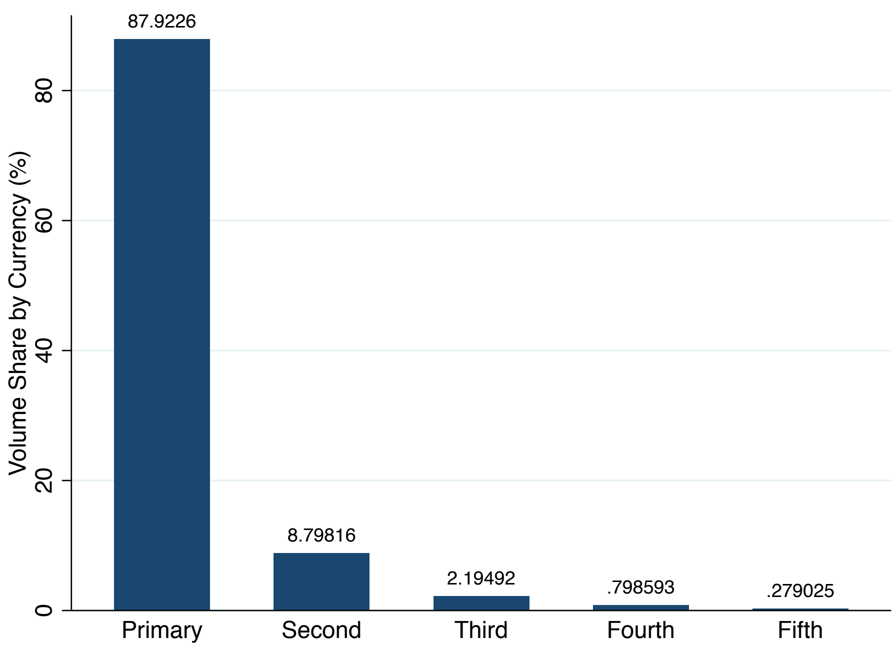


Figure A.6: Average Volume Share in Top 5 Trading Pairs

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

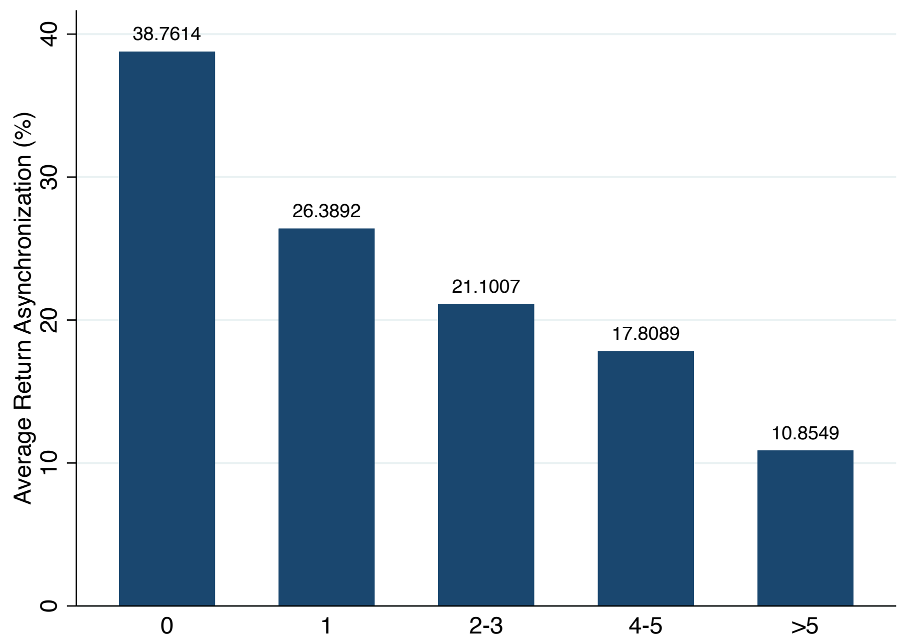


Figure A.7: Average Return Asynchronization and Number of Top Exchanges by Currency

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

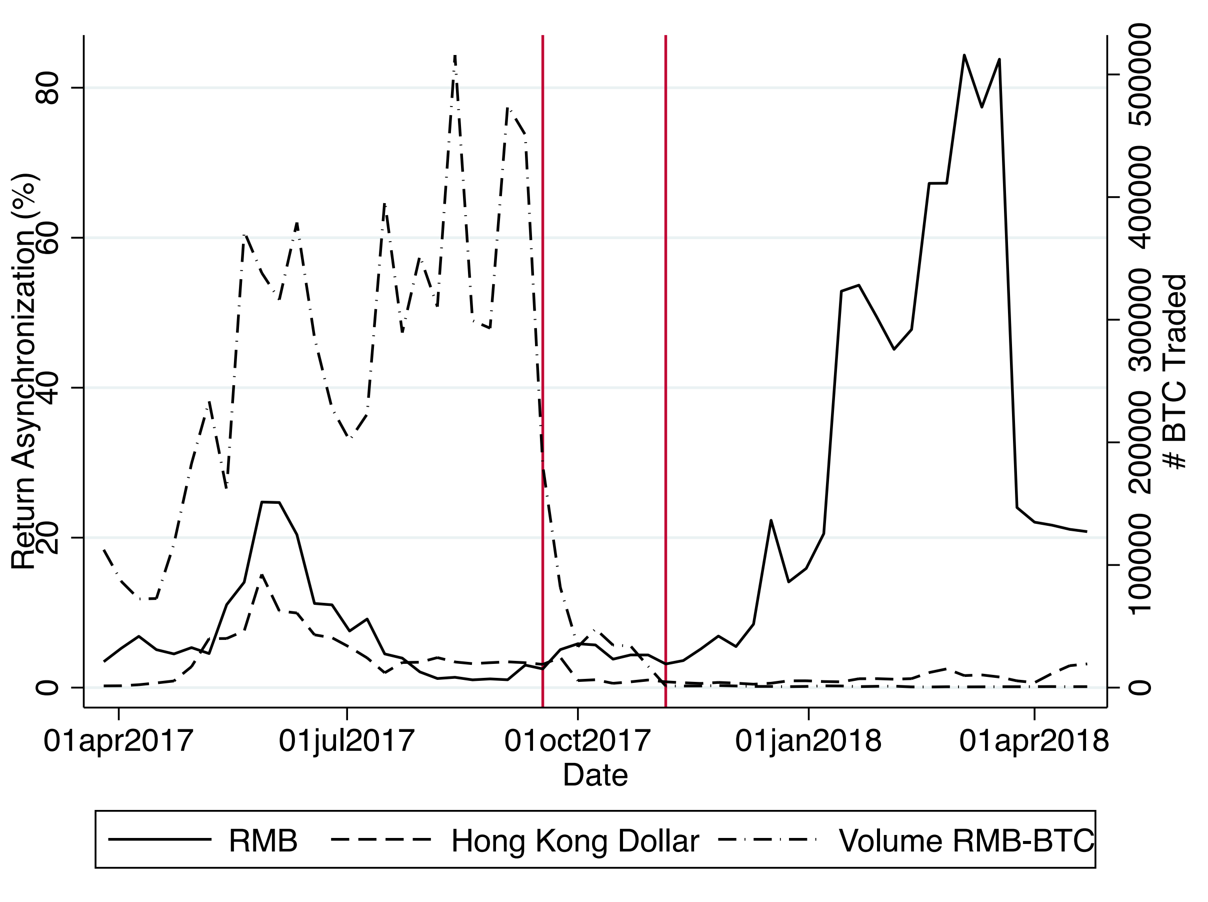


Figure A.8: China Ban - Friction

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

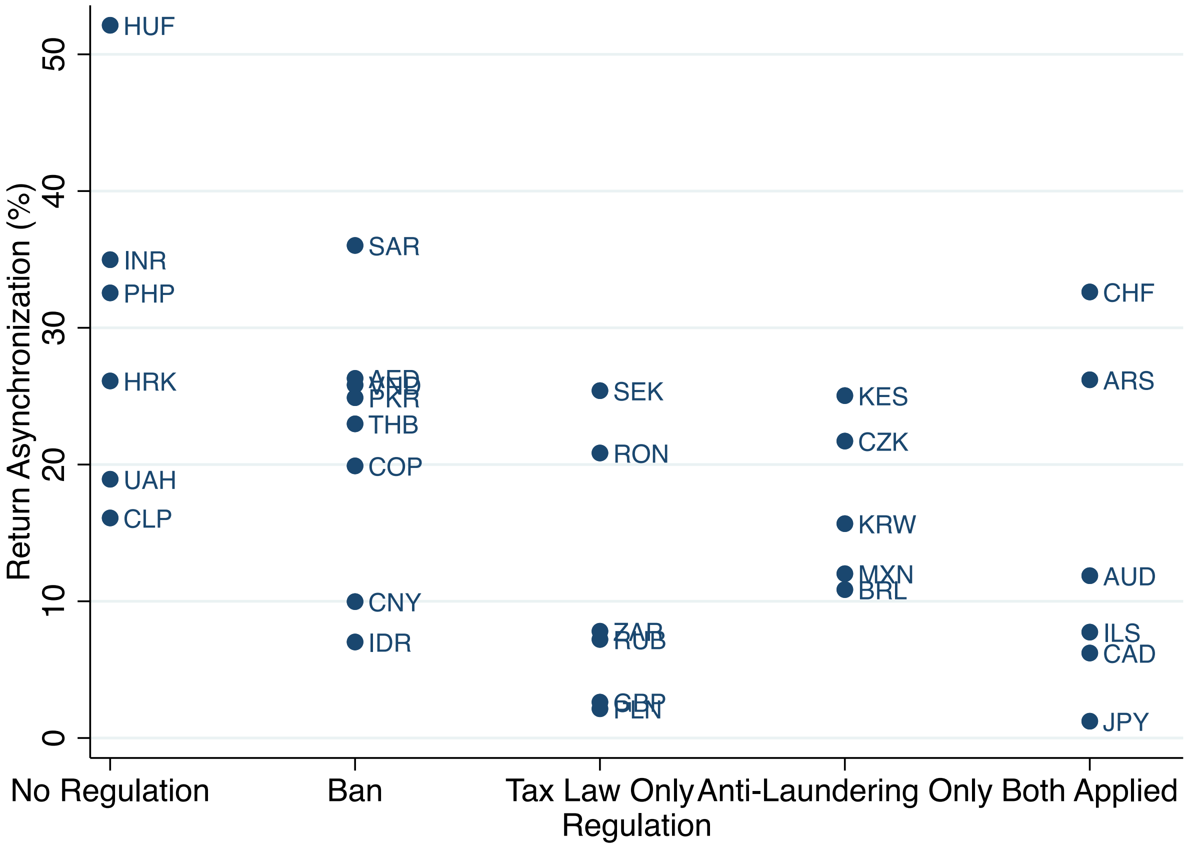


Figure A.9: Return Asynchronization and Law

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

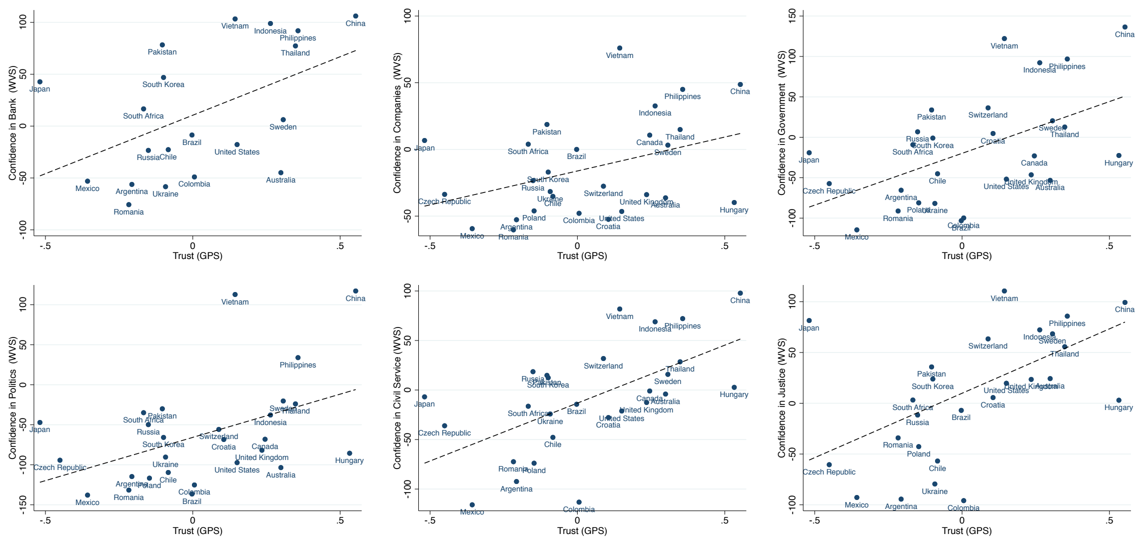


Figure A.10: Trust and Confidence in Institutions

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

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

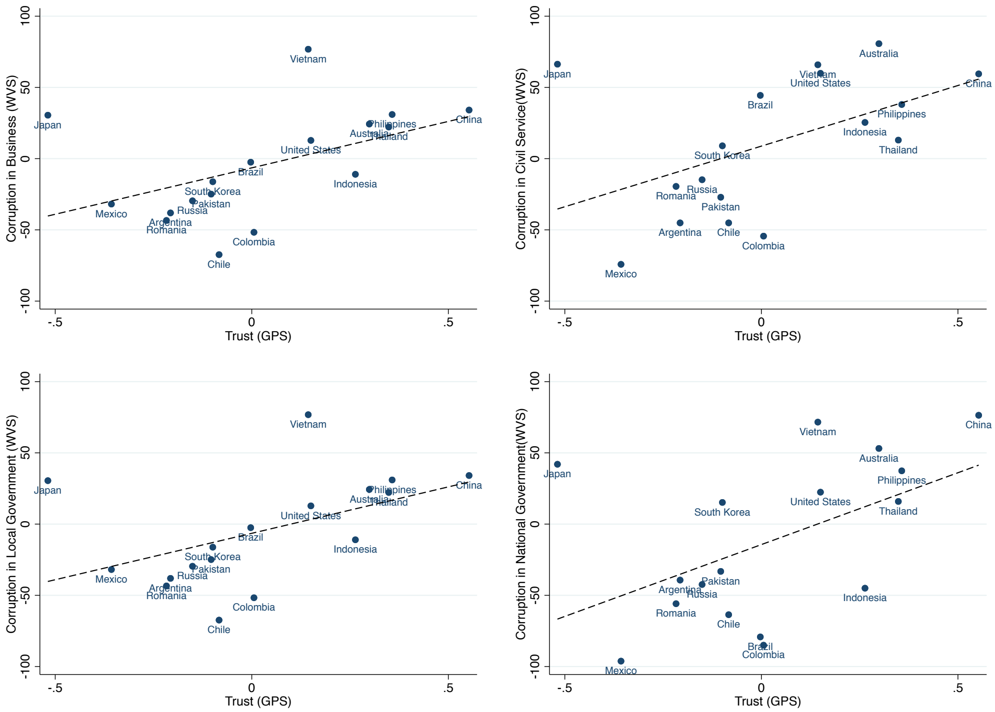


Figure A.11: Perceived Corruption and Trust

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

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

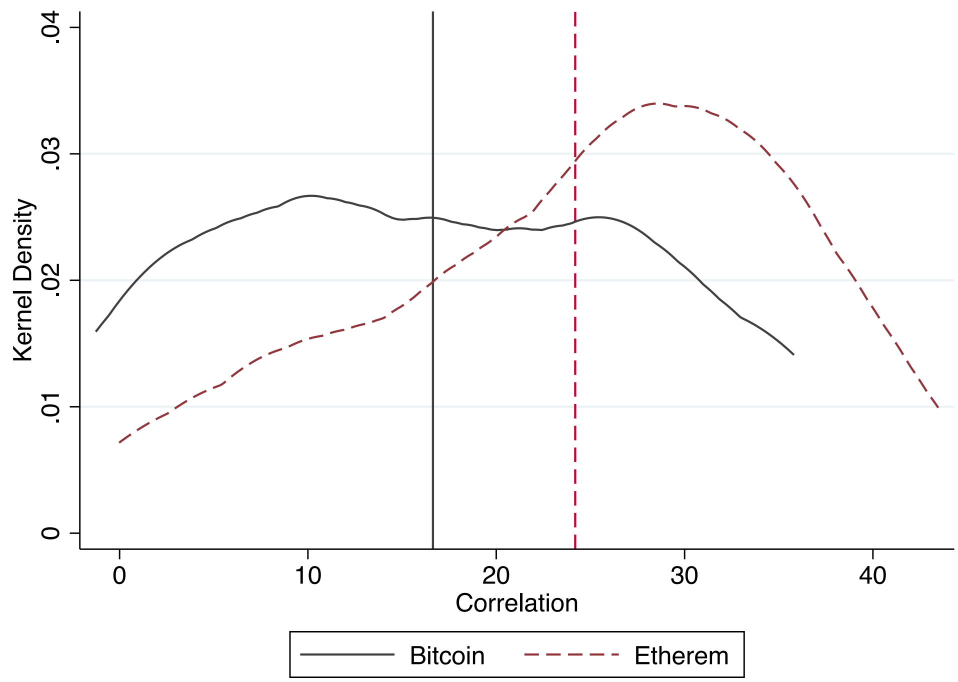


Figure A.12: Kernel Density of Correlation between Returns of Stock and Crypto

Notes: This figure plots the kernel density of the correlation between stock index returns and cryptocurrency US dollar returns. The black solid vertical line indicates the average correlation between domestic stock returns and Bitcoin returns. The red dashed vertical line represents the average correlation between domestic stock returns and Ethereum returns.

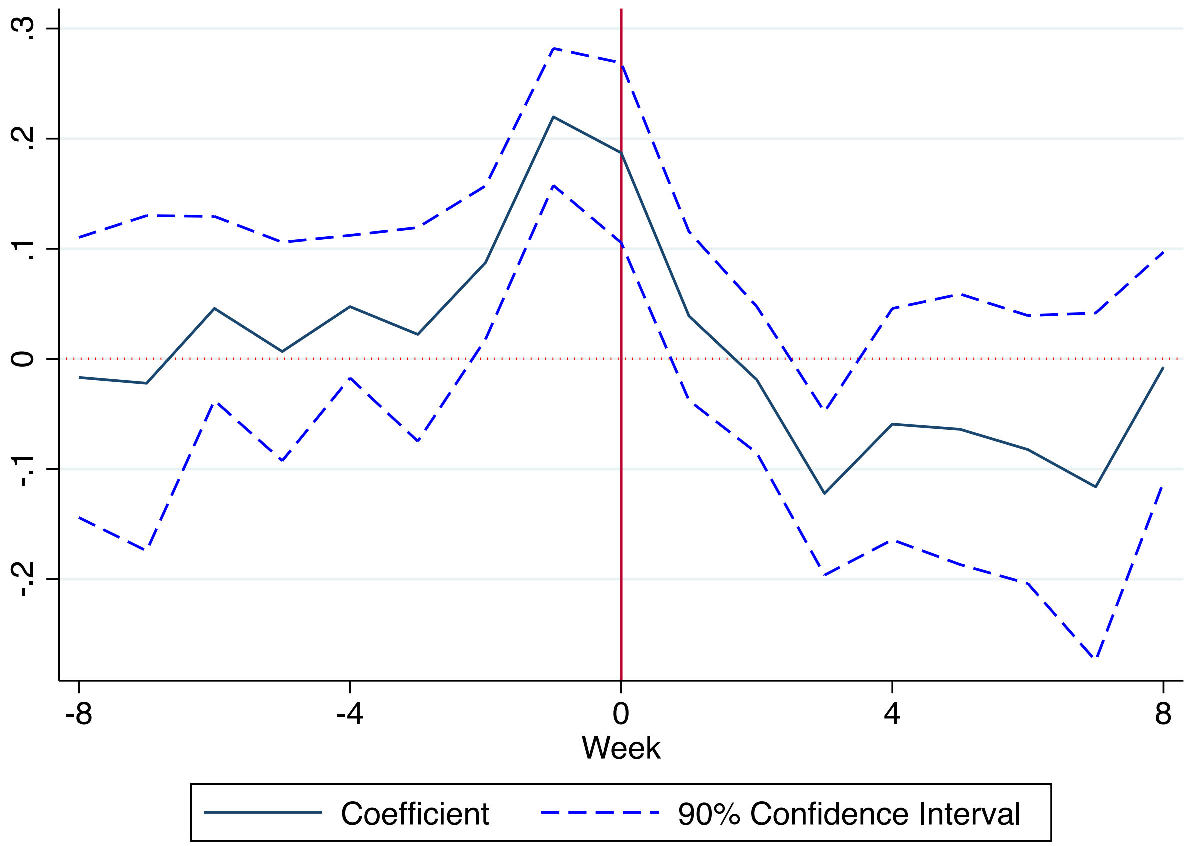


Figure A.13: Exchange Rate and Price Deviation

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

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

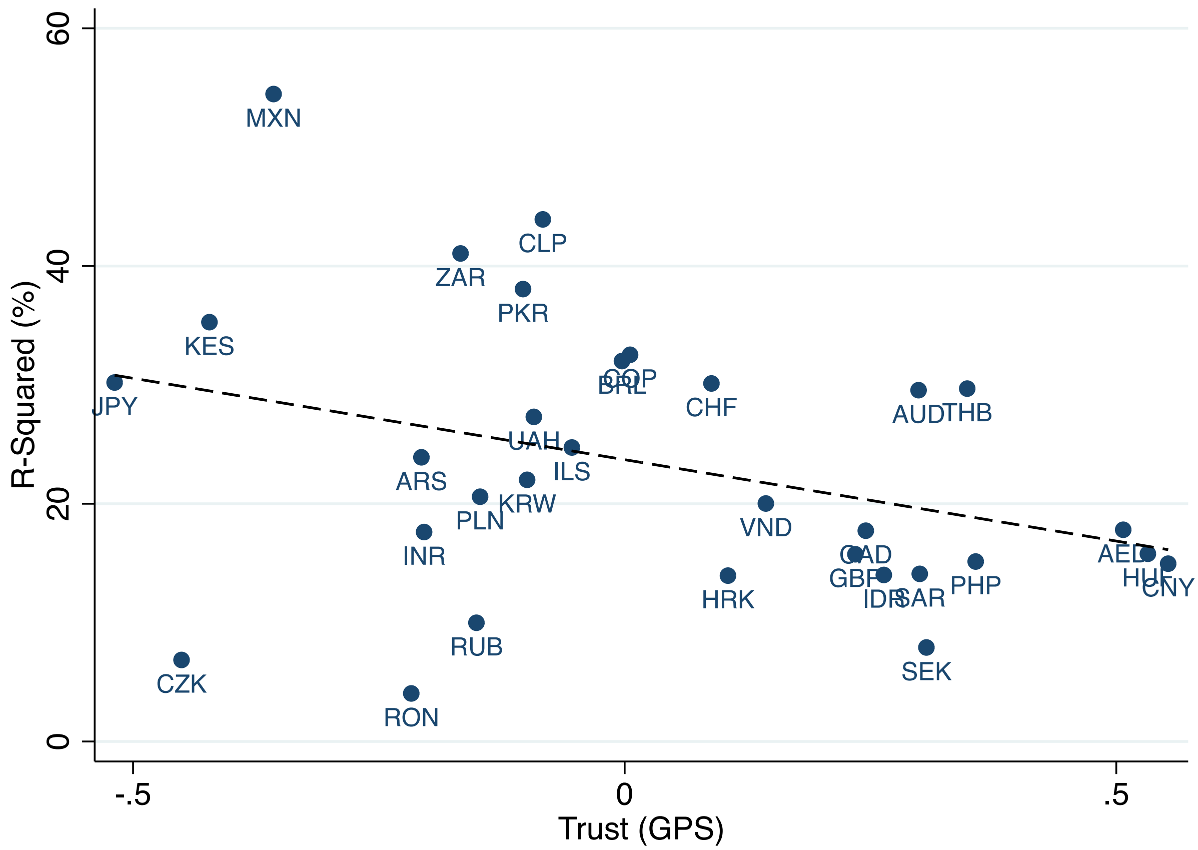


Figure A.14: In-sample R-squared and Trust

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

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

where the eight factors include four Google search indices for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

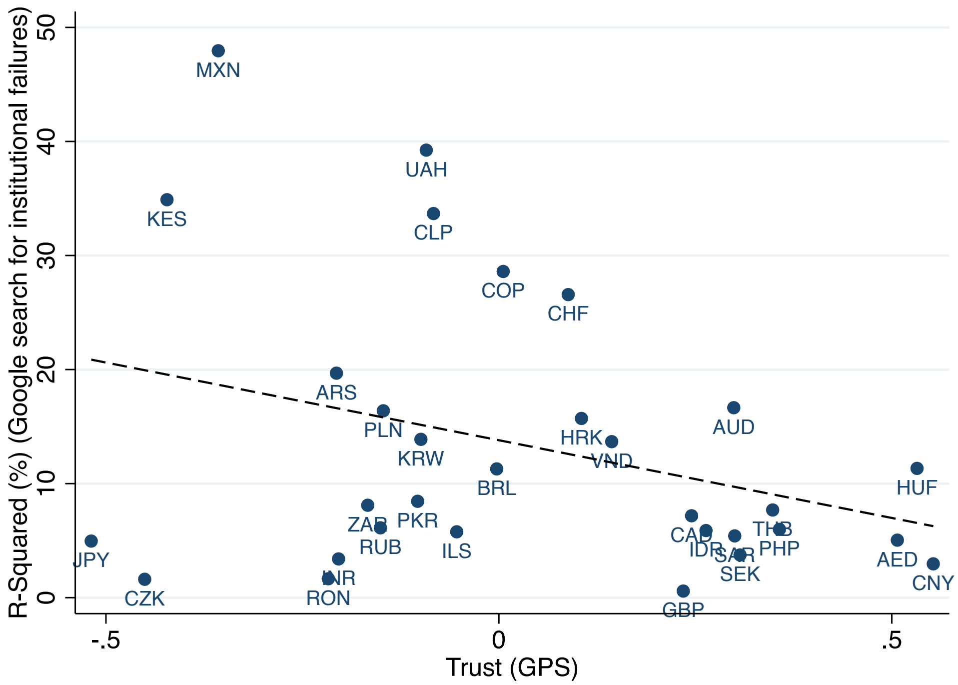
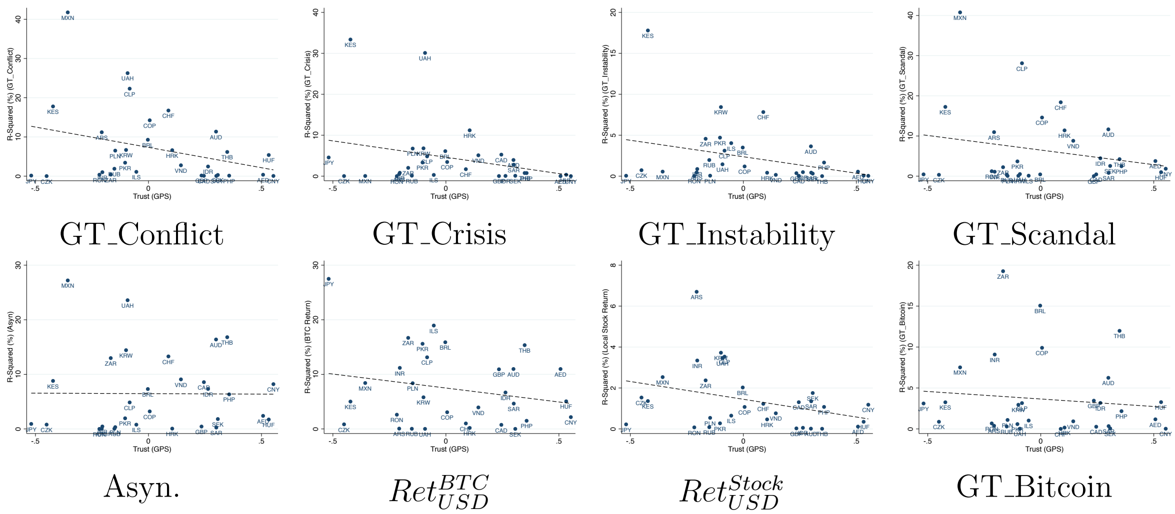


Figure A.15: In-sample R-squared and Trust (Google Search for Institutional Failures)

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

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

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



GT_Conflict GT_Crisis GT_Instability GT_Scandal

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

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

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

$$\widehat{Deviation_t} = \alpha + \beta X_{c,t} + \epsilon_t$$

$X_{i,t}$ denotes each of the eight factors: Google search indices for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Table A.1: Bitcoin Residual Trading Volume and Trust Level

	Residual Log Volume			Residual Volume per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust	-4.560***	-4.373***	-4.828***	-21.40***	-21.19**	-25.86***
	(-3.62)	(-3.05)	(-3.07)	(-2.86)	(-2.48)	(-3.06)
Legal Status		0.432	0.0283		2.180	0.367
		(0.61)	(0.04)		(0.52)	(0.08)
Tax Laws		0.310	-0.390		-2.434	-6.646
		(0.35)	(-0.38)		(-0.46)	(-1.20)
Anti-Money Laundering		0.342	-0.0748		1.959	-0.816
		(0.93)	(-0.17)		(0.89)	(-0.33)
Capital Controls			-0.322			-3.294
			(-0.35)			(-0.66)
Credit			0.0114			0.102**
			(1.69)			(2.81)
R-squared	31.14%	34.40%	40.62%	22.03%	25.05%	47.96%
# Currencies	31	31	28	31	31	28

Notes: This table reports the relationship between trust and residual 2019 Bitcoin trading volume. The residual trading volume is the error term estimated from the following regression:

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

The independent variable is residual 2019 Bitcoin trading volume in Columns (1)-(3), and residual 2019 Bitcoin trading volume per capita in Columns (4)-(6). Columns (1) and (4) reports the results from the uni-variate regression:

$$\widehat{Vol_c} = \beta Trust_c + \gamma + \epsilon_c$$

Columns (2) and (5) include three variables on cryptocurrency regulations: legal status, tax laws, and anti-money laundering regulations. Columns (3) and (6) add capital controls and credit by financial sector (% GDP) in the regressions. Three countries are missing in Columns (3) and (6): the United Arab Emirates and Croatia do not have data in capital controls, Canada does not provide credit data in World Development Indicators. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Correlation Matrix of Cumulative Google Search Indices

	Conflict	Crisis	Instability	Scandal
Conflict	100%			
Crisis	19.32%	100%		
Instability	48.58%	-3.57%	100%	
Scandal	11.73%	7.80%	-10.21%	100%
Mean	188.11	148.32	127.32	165.24
S.D.	65.06	59.22	67.45	55.06

Notes: This table reports the correlation, mean, and standard deviation of cumulative Google search indices of four keywords: "conflict," "crisis," "instability," and "scandal". The raw indices range from 0 to 100. The maximum score is set as 100 by Google. The cumulative Google search index is defined as the eight-week discounted sum with a rate of 0.8:

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

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

Table A.3: Shortlisted Events of Google Search Spikes

Country	Period	Keyword	Event
Brazil	Dec 2017	Crisis	Standard and Poor's reduces Brazil's credit rating from BB to BB-
Korea	Oct 2016	Scandal	Widespread coverage of 2016 South Korean political scandal began
Indonesia	Dec 2017	Conflict	Mimika blockade: Tensions developed in Mimika Regency of Papua
Poland	Nov 2017	Crisis, Conflict, Instability	White nationalists call for ethnic purity at Polish demonstration
Chile	Oct 2019	Crisis	Civil protests have taken place throughout Chile
Russia	Dec 2017	Conflict	The Russian military intervention in the Syrian Civil War
Russia	Oct 2018	Instability	Nuclear missiles tensions between US and Russia are placed in Europe
Russia	Feb 2017	Scandal	Donald Trump's Russia scandal got started
Japan	Feb 2017	Scandal	The land sale scandal of central government of Japan
UK	May 2018	Scandal	The 2018 Windrush scandal & Jeremy Hunt property scandal
UK	Sep 2015	Scandal	Prime Minister Cameron's drug and honesty scandal
Brazil	Feb & Mar 2015	Crisis, Scandal	Petrobras corruption scandal
Argentina	May & Sep 2018	Crisis	Argentine monetary crisis
Mexico	Oct & Nov 2016	Crisis	Trump's election and policy
Ukraine	Feb 2014	Crisis, Conflict	Political crisis & Change of hryvnia as floating currency
Colombia	Aug 2015	Crisis	Oil price decline & Colombian peso depreciation
Russia	Mar 2014	Crisis	Oil price decline & International sanction & Political rent

Notes: A shortlist of events matched with peaks in Google Trends. In total, 121 surges emerge in the four keywords: Conflict, Crisis, Instability, and Scandal. 95 surges can be found with concrete events, while we cannot tie events to the other 26 spikes.

Table A.4: Robustness: Price Deviation Response to Institutional Failures

	Dependent Variable: *Deviation* (bps)			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	2.617**	1.216*	2.173**	1.951***
	(2.64)	(1.90)	(2.43)	(2.76)
$Ret^{BTC}_{USD,t-9\to t-1}$	145.9***	153.6***	165.1***	165.3***
	(3.06)	(3.30)	(3.54)	(3.60)
$Ret^{Currency}_{c,t-9\to t-1}$	732.5	645.3	636.9	544.7
	(1.69)	(1.44)	(1.48)	(1.29)
# observations	7,843	7,843	7,843	7,843

Notes: This table reports the robustness check. Bitcoin 8-week returns and currency exchange rate 8-week returns are included in the panel regression. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Ret^{BTC}_{USD,t-9\to t-1} + \beta_3 Ret^{Currency}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the cumulative Google search indices of four keywords: "conflict," "crisis," "instability," and "scandal".

Table A.5: Robustness: Attention to Bitcoin and Institutional Failures

	Dependent Variable: $\Delta GT\_Bitcoin_t$			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	0.0711***	0.0716***	0.0589***	0.0348***
	(5.02)	(3.79)	(3.48)	(3.49)
$Ret^{BTC}_{USD,t-9\to t-1}$	42.35***	42.34***	42.92***	42.88***
	(31.78)	(31.41)	(31.53)	(30.93)
$Ret^{Currency}_{c,t-9\to t-1}$	-29.56	-30.83	-31.61	-33.96
	(-1.27)	(-1.29)	(-1.42)	(-1.48)
$Ret^{Stock}_{c,t-9\to t-1}$	3.031	3.064	2.891	3.717
	(0.65)	(0.68)	(0.71)	(0.82)
# observations	7,688	7,688	7,688	7,688

Notes: This table reports the response of "Bitcoin" Google search growth to four institutional failures ("Conflict," "Crisis," "Instability," and "Scandal") controlling for past eight-week Bitcoin returns, past eight-week currency returns, and past eight-week stock market returns.

$$\Delta GT\_Bitcoin_{c,t} = \beta_1 GT_{c,t} + \beta_2 Ret^{BTC}_{USD,t-9\to t-1} + \beta_3 Ret^{Currency}_{c,t-9\to t-1} + \beta_4 Ret^{Stock}_{c,t-9\to t-1} + \gamma_c + \epsilon_{c,t}$$

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

Table A.6: Attention to "Gold" and Institutional Failures

	Dependent Variable: GT_Gold			
	(1) Conflict	(2) Crisis	(3) Instability	(4) Scandal
Google Trend Index	0.0202	0.0125	0.0126	-0.0116
	(1.40)	(1.38)	(1.18)	(-1.39)
# observations	7,688	7,688	7,688	7,688

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

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

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

Table A.7: Robustness: Heterogeneous Response to Google Trend

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$GT\_Conflict$	1.323**	0.0166	2.515	2.510**	-2.919*
	(2.07)	(0.05)	(1.31)	(2.77)	(-2.02)
$GT\_Conflict \times Distrust$					4.494**
					(2.59)
$GT\_Instability$	2.133**	2.415	1.229	2.721*	3.486
	(2.38)	(1.32)	(0.75)	(2.18)	(0.83)
$GT\_Instability \times Distrust$					-1.377
					(-0.35)
$GT\_Scandal$	1.713***	1.187***	2.739***	1.485***	1.439
	(8.39)	(4.55)	(5.88)	(4.30)	(1.40)
$GT\_Scandal \times Distrust$					1.196***
					(4.03)
# observations	7,843	2,783	2,277	2,783	7,843
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to Google searches in "Crisis", "Instability", and "Scandal", and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Table. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A.8: Horsing Racing with Other Country Features

	Dependent Variable: *Deviation*					
	(1)	(2)	(3)	(4)	(5)	(6)
Covariate	N/A	GDP	Credit	Law	Gov Eff	Corruption
GT_Crisis	-5.469**	-3.564***	-4.099***	-4.700***	-4.748***	-4.797***
	(-2.32)	(-4.09)	(-3.52)	(-4.18)	(-4.34)	(-4.22)
GT_Crisis × *Distrust*	8.530***	6.874***	5.679***	4.521***	4.557***	4.459***
	(2.95)	(3.04)	(3.15)	(4.10)	(3.95)	(4.22)
GT_Crisis × *Covariate*		-0.311	-0.013	-0.412	-0.328	-0.224
		(-1.53)	(-1.09)	(-0.47)	(-0.35)	(-0.32)
# observations	7,843	7,843	7,590	7,843	7,843	7,843

Notes: This table reports the horse-racing of trust with other country features, including GDP per capita, credit by the financial sector, the rule of law, government effectiveness, and corruption control scores.

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

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

Table A.9: Price Deviation Response to Ethereum Return

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Medium-trust	(4) Low-trust	(5) Full
$Ret^{ETH}_{USD,t-9\rightarrow t-1}$	0.212	-0.0974	0.308	0.444**	-0.896**
	(1.43)	(-0.43)	(0.85)	(2.40)	(-2.05)
$Ret^{ETH}_{USD,t-9\rightarrow t-1} \times Distrust$					1.146***
					(2.95)
# observations	6,973	2,475	2,023	2,475	6,973
Currency FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the price responses to the past eight-week Ethereum return and the heterogeneous effects by country's trust level. High-trust countries refer to 11 countries with GPS trust score above 0.2. Medium-trust countries refer to 9 countries with a trust score between -0.1 and 0.2. Low-trust countries refer to 11 countries with a trust score below -0.1. Robust standard errors are clustered at the currency level. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A.10: Return Asynchronization and Capital Controls

	Dependent Variable: Return Asynchronization					
	Capital Controls		Retail Transfer Costs			
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Controls	7.504*					
	(1.95)					
i.Gate		10.22				
		(1.60)				
i.Wall		15.40*				
		(1.97)				
Exchange Rate Margin			0.873		-2.288	
			(0.45)		(-0.78)	
Transaction Fee				-0.583		-0.285
				(-0.49)		(-0.62)
R-squared	12.38%	13.34%	0.76%	0.88%	5.75%	3.67%
# Currencies	29	29	29	29	12	12

Notes: This table reports the impacts of capital controls and retail money transfer costs on return asynchronization. The capital control measure is from Fernández et al. (2016): In Column (1), we assign 1 to "Open" category, 2 to "Gate" category, and 3 to "Wall" category. In Column (2), the "Open" category is the missing group; i.Gate and i.Wall are two indicators for the "Gate" and "Wall" categories. Retail transfer costs are collected from Monito.com and the World Bank remittance survey. Column (3) - (4) report the results based on data from Monito.com, and Column (5) - (6) report the results based on data from World Bank remittance survey. The exchange rate margin refers to the markup paid to the service provider per unit of fund transferred. The transaction fee refers to the fixed cost per transaction charged by the service provider.

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

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

Table A.11: Return Asynchronization and Regulations

	Return Asynchronization (%)			
	(1)	(2)	(3)	(4)
Regulate or not	-13.50***			
	(-3.34)			
Legal Status		5.712**		
		(2.12)		
Tax Laws			-7.202*	
			(-1.88)	
Anti-Money Laundering				-2.984
				(-0.72)
# Currencies	31	25	25	25

Notes: This table reports the relationship between return asynchronization and regulations. We classify the regulatory status into four categories. "Regulate or not" dummy is one if the country has any specific regulation for cryptocurrency; otherwise, zero. "Legal Status" dummy is one if regulators ban cryptocurrency; otherwise, zero. "Tax Laws" dummy is one if tax laws apply to cryptocurrency; otherwise, zero. "Anti-Money Laundering" dummy is one if the country announces anti-money laundering laws for cryptocurrency; otherwise, zero.

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

where $\overline{Asyn_c}$ is the average return asynchronization in country c. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Trust and Confidence in Institutions

	(1) Bank	(2) Company	(3) Government	(4) Politics	(5) Civil Service	(6) Justice
Trust	112.7**	50.83**	128.1***	108.1**	117.0***	119.3***
	(2.40)	(2.10)	(3.05)	(2.59)	(3.69)	(3.11)
R-squared	24.21%	15.03%	27.12%	21.17%	35.29%	28.72%
# Currencies	20	27	27	27	27	26

Notes: This table reports the relationship between trust and confidence in institutions, including banks, companies, government, politics, civil service, and justice. The trust measure is from the Global Preference Survey, and the confidence scores are calculated from the Global Value Survey. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A.13: Trust and Corruption in Institutions

	(1) Business	(2) Civil Service	(3) Local Gov.	(4) State Gov.
Trust	65.17**	85.10**	100.9**	69.73*
	(2.15)	(2.18)	(2.25)	(1.92)
R-squared	23.49%	24.10%	25.22%	19.68%
# Currencies	17	17	17	17

Notes: This table reports the relationship between trust and the perceived corruption control in business, civil service, the local government, and the state government. The trust measure is from the Global Preference Survey, and the corruption control scores are calculated from the World Value Survey. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A.14: Trust Validation

	(1) Most Trusted	(2) Know Personally	(3) Neighbors	(4) First Met
Trust	20.92*	67.13*	60.38**	46.24
	(2.01)	(1.96)	(2.31)	(1.51)
R-squared	13.43%	15.47%	20.31%	9.78%
# observations	17	17	17	17

Notes: This table validates the correlation between trust in the Global Preference Survey (GPS) and trust variables in the World Value Survey (WVS):

$$Trust_c^{WVS} = \beta Trust_c^{GPS} + \alpha + \epsilon_c$$

WVS's trust measures include general trust in most people, trust people you know personally, trust in your neighbors, and trust people you first met. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

	Dependent Variable: $Ret^{Crypto}_{t-9\rightarrow t-1}$			
	Weekly		Monthly	
	BTC	ETH	BTC	ETH
	(1)	(2)	(3)	(4)
$Ret^{Stock}_{c,t-9\rightarrow t-1}$	0.239***	0.494***	1.394**	2.922**
	(4.94)	(4.65)	(2.15)	(2.02)
# observations	8,176	6,965	264	225
$Asyn_c$	5.45%	5.56%	13.18%	13.39%

Notes: This table reports uni-variate regressions of log stock returns on log BTC/ETH returns in the past eight weeks. Columns (1) and (2) estimate with panel data (at currency by week level). Columns (3) and (4) estimate with time-series data (equal-weighted collapsing stock returns to obtain weekly data). Raw correlations are reported for each specification. t-stats are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A.16: Price Deviation Regressions with Currency Return Controls

	Dependent Variable: $Deviation_{c,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GT_Crisis	2.678**	2.687**						
	(2.71)	(2.71)						
$Asyn_c$			5.999***	6.038***				
			(4.69)	(4.70)				
$Ret^{BTC}_{USD,t-9\to t-1}$					119.4**	115.3**		
					(2.75)	(2.67)		
$Ret^{Stock}_{c,t-9\to t-1}$							237.8**	223.1**
							(2.24)	(2.11)
$Ret^{Currency}_{c,t}$		1787.8***		2045.3***		1784.4***		1836.5***
		(3.81)		(3.98)		(3.85)		(3.71)
$Ret^{Currency}_{c,t-1}$		2255.0***		2207.9***		1876.3***		1940.1***
		(4.93)		(5.43)		(4.41)		(4.61)
# observations	7,843	7,843	8,060	8,060	8,060	8,060	8,060	8,060

Notes: This table examines the impacts of exchange rate on main specifications. Columns (1), (3), (5), and (7) report uni-variate regressions on $X_{c,t}$: Google Trend index of keyword "Crisis", return asynchronization, Bitcoin past 8-week returns, and local stock 8-week returns. In Columns (2), (4), (6), and (8), we add simultaneously, and one-week lagged exchange rate returns as the following:

$$Deviation_{c,t} = \beta X_{c,t} + \kappa_1 Ret^{Currency}_{c,t} + \kappa_2 Ret^{Currency}_{c,t-1} + \gamma_c + \epsilon_{c,t}$$

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

Table A.17: Predictability in FX Exchange Rates

	Dependent Variable: $FX_{c,t}$				
	(1) CIP	(2) 1-week FX Ret	(3) 8-week FX Ret	(4) 24-week FX Ret	(5) Dummy (24-week Ret < -15%)
$Deviation_{c,t}$	3.06×10^{-8}	0.00427	-0.00447	-0.0296	5.77×10^{-6}
	(0.35)	(0.71)	(-0.80)	(-1.18)	(1.00)
# observations	4,420	8,029	7,812	7,316	7,316

Notes: This table explores whether price deviations predict anything in the FX market.

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

$FX_{c,t}$ stands for Libor-based deviations from covered interest parity (CIP) in Column (1), the future one-week exchange rate return in Column (2), the future 8-week exchange rate return in Column (3), the future 24-week exchange return in Column (4), and the dummy for massive currency depreciation in next 24 weeks (24-week Ret < -15%) in Column (5). The construction of CIP deviation follows Du et al. (2018). The Libor basis is equal to:

$$y_{t,t+n}^{USD,Libor} - (y_{t,t+n}^{c,Libor} - \rho_{t,t+n})$$

where $n =$ three months, $y_{t,t+n}^{USD,Libor}$ and $y_{t,t+n}^{c,Libor}$ denote the US and foreign three-month Libor rates, and $\rho_{t,t+n} \equiv \frac{1}{n}(f_{t,t+n} - s_t)$ denotes the forward premium obtained from the forward $f_{t,t+n}$ and the spot s_t exchange rates. With Bloomberg data, we can construct CIP deviations for 17 out of 31 countries. t-stats are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: In-sample R-Squared Analysis (Individual factor)

	Dependent Variable: $\widehat{Deviation}$			
	(1)	(2)	(3)	(4)
	All Countries	High-trust	Medium-trust	Low-trust
$GT\_Conflict$	1.66%	0.00615%	5.94%	2.81%
GT_Crisis	0.429%	0.0389%	0.659%	1.35%
$GT\_Instability$	0.16%	0.121%	0.132%	0.244%
$GT\_Scandal$	1.41%	0.126%	4.68%	1.18%
$Asyn_c$	2.82%	3.04%	7.64%	0.0499%
$Ret^{BTC}_{USD,t-9\to t-1}$	2.24%	0.486%	2.71%	4.85%
$Ret^{Stock}_{c,t-9\to t-1}$	0.161%	0.0388%	0.12%	1.68%
$GT\_Bitcoin$	0.655%	0.0253%	1.25%	1.61%
Average	1.192%	0.485%	2.891%	1.722%
# observations	7,645	2,722	2,225	2,698

Notes: This table reports the R-Squared of the investment factor analysis on price deviation for all coutries, high-trust countries, medium-trust countries, and low-trust countries:

$$\widehat{Deviation}_{c,t} = \beta X_{c,t} + \gamma + \epsilon_t$$

where $\widehat{Deviation}_{c,t}$ is the demeaned price deviation by each country c, and $X_{c,t}$ denotes each of the eight factors: four Google searches of institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

Table A.19: In-sample R-Squared Analysis (Multi-factor)

	Dependent Variable: $\widehat{Deviation}$				
	(1)	(2)	(3)	(4)	(5)
$Asyn_c$	2.794***	2.574***	2.711***	2.709***	2.745***
	(13.03)	(11.73)	(12.49)	(12.47)	(12.64)
$GT\_Conflict$		0.455***	0.383***	0.382***	0.399***
		(4.21)	(3.58)	(3.57)	(3.73)
GT_Crisis		0.0939	0.0326	0.0314	0.0339
		(0.92)	(0.32)	(0.31)	(0.34)
$GT\_Instability$		0.122	0.171	0.170	0.155
		(1.11)	(1.57)	(1.56)	(1.43)
$GT\_Scandal$		0.672***	0.687***	0.687***	0.677***
		(5.99)	(6.19)	(6.19)	(6.11)
$Ret^{BTC}_{USD,t-9\rightarrow t-1}$			199.7***	197.4***	196.5***
			(13.70)	(12.06)	(12.01)
$GT\_Bitcoin$				0.0526	0.0471
				(0.30)	(0.27)
$Ret^{Stock}_{c,t-9\rightarrow t-1}$					212.2***
					(3.90)
R^2	0.0282	0.0393	0.0617	0.0617	0.0635
# observations	7,645	7,645	7,645	7,645	7,645

Notes: This table reports the multi-factor analysis on price deviation for all 31 countries:

$$\widehat{Deviation_{c,t}} = \sum_i \beta X^i_{c,t} + \gamma + \epsilon_t$$

where $\widehat{Deviation_{c,t}}$ is the demeaned price deviation by each country c, and $X^i_{c,t}$ denotes each of the eight factors: four Google search for institutional failures ("Conflict," "Crisis," "Instability," and "Scandal"), Google searches for "Bitcoin", return asynchronization, past eight-week Bitcoin returns, and past eight-week local stock market returns.

B Chapter 1: Theory Appendix

B.1 Proof of Proposition 1: Local Risky Weight

We consider the two-asset case: investors choose the optimal share of wealth to invest in the local risk asset by solving the following utility maximization problem:

$$\begin{aligned}
\max_{\pi_{L,t}} logE_t[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}] &= \max_{\pi_{L,t}} log\{E[p\frac{W_c^{1-\gamma}}{1-\gamma} + (1-p)\frac{W_{nc}^{1-\gamma}}{1-\gamma}]\} \\
&= \max_{\pi_{L,t}} log\{E_t[pe^{(1-\gamma)w_{t+1,c}} + (1-p)e^{(1-\gamma)w_{t+1,nc}}]\} \\
&= \max_{\pi_{L,t}} log\{E_t[pe^{(1-\gamma)r_{p,t+1,c}} + (1-p)e^{(1-\gamma)r_{p,t+1,nc}}]\} \\
&= \max_{\pi_{L,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,nc}}[1-p+pe^{(1-\gamma)(r_{p,t+1,c}-r_{p,t+1,nc})}]\} \\
&= \max_{\pi_{L,t}} log\{E_t e^{(1-\gamma)r_{p,t+1,nc}}[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&= \max_{\pi_{L,t}} logE_t e^{(1-\gamma)r_{p,t+1,nc}} + logE_t[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&= \max_{\pi_{L,t}} logE_t e^{(1-\gamma)r_{p,t+1,nc}} + logE_t[1-p+pe^{(1-\gamma)(\pi_{L,t}b+\frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2)}]\} \\
&\approx \max_{\pi_{L,t}} \underbrace{\pi_{L,t}(\mu_L - r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_L^2 + \frac{1}{2}(1-\gamma)\pi_{L,t}^2\sigma_L^2}_{\text{Financial Component}} + \underbrace{p[\pi_{L,t}(\bar{b} + \frac{1}{2}\sigma_b^2) - \frac{1}{2}\gamma\pi_{L,t}^2\sigma_b^2]}_{\text{Trust Component}}
\end{aligned}$$

The first part is the optimization problem purely from the financial component, and the second part comes from the distrust loss. Then, we can solve the optimal investment in the local risky asset:

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

In the derivation, we use $w_{t+1,nc} = r_{p,t+1,nc} + w_t$, $w_{t+1,c} = r_{p,t+1,c} + w_t$, and the difference between portfolio returns in the cheat and non-cheat states can be derived with the following approximations:

$$r_{p,t+1,nc} - r_{f,t+1} = log(1 + \pi_{L,t}(exp(r_{L,t+1} - r_{f,t+1}) - 1)) \approx \pi_{L,t}(r_L - r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_L^2$$

$$r_{p,t+1,c} - r_{f,t+1} \approx log(1 + \pi_{L,t}(exp(r_{L,t+1} + b - r_{f,t+1}) - 1)) \approx \pi_{L,t}(r_L + b - r_f) + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})(\sigma_L^2 + \sigma_b^2)$$

$$r_{p,t+1,c} - r_{p,t+1,nc} = \pi_{L,t}b + \frac{1}{2}\pi_{L,t}(1-\pi_{L,t})\sigma_b^2$$

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

We extend the framework into the multiple risky assets:

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

π_t is a vector of wealth share invested by asset. $\boldsymbol{\Sigma}$ is the *conditional* variance-covariance matrix, $\boldsymbol{r}_{t+1}$ is the vector of returns, $\boldsymbol{p}$ and $\boldsymbol{\sigma}_b^2$ are diagonal matrices with the cheating probability and the variance of cheating magnitude for each asset, $\bar{\boldsymbol{b}}$ is a vector of average cheating magnitude for each asset, ι is a vector of ones.

The optimal portfolio holdings

$$\pi_t = \frac{1}{\gamma}(\boldsymbol{\Sigma} + \boldsymbol{\sigma}_b^2)^{-1}[\boldsymbol{r}_{t+1} + \boldsymbol{p}\bar{\boldsymbol{b}} - rf_{t+1}\boldsymbol{\iota} + \frac{1}{2}(\boldsymbol{\sigma}_t^2 + \boldsymbol{\sigma}_b^2\boldsymbol{p})]$$

Particularly, we are interested in the case with one local risky asset and one global risky asset:

$$\pi_t = \begin{bmatrix} \pi_L \\ \pi_G \end{bmatrix} \text{ and } \boldsymbol{p} = \begin{bmatrix} p & 0 \\ 0 & 0 \end{bmatrix}$$

Then, we can express the portfolio weights as the following:

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

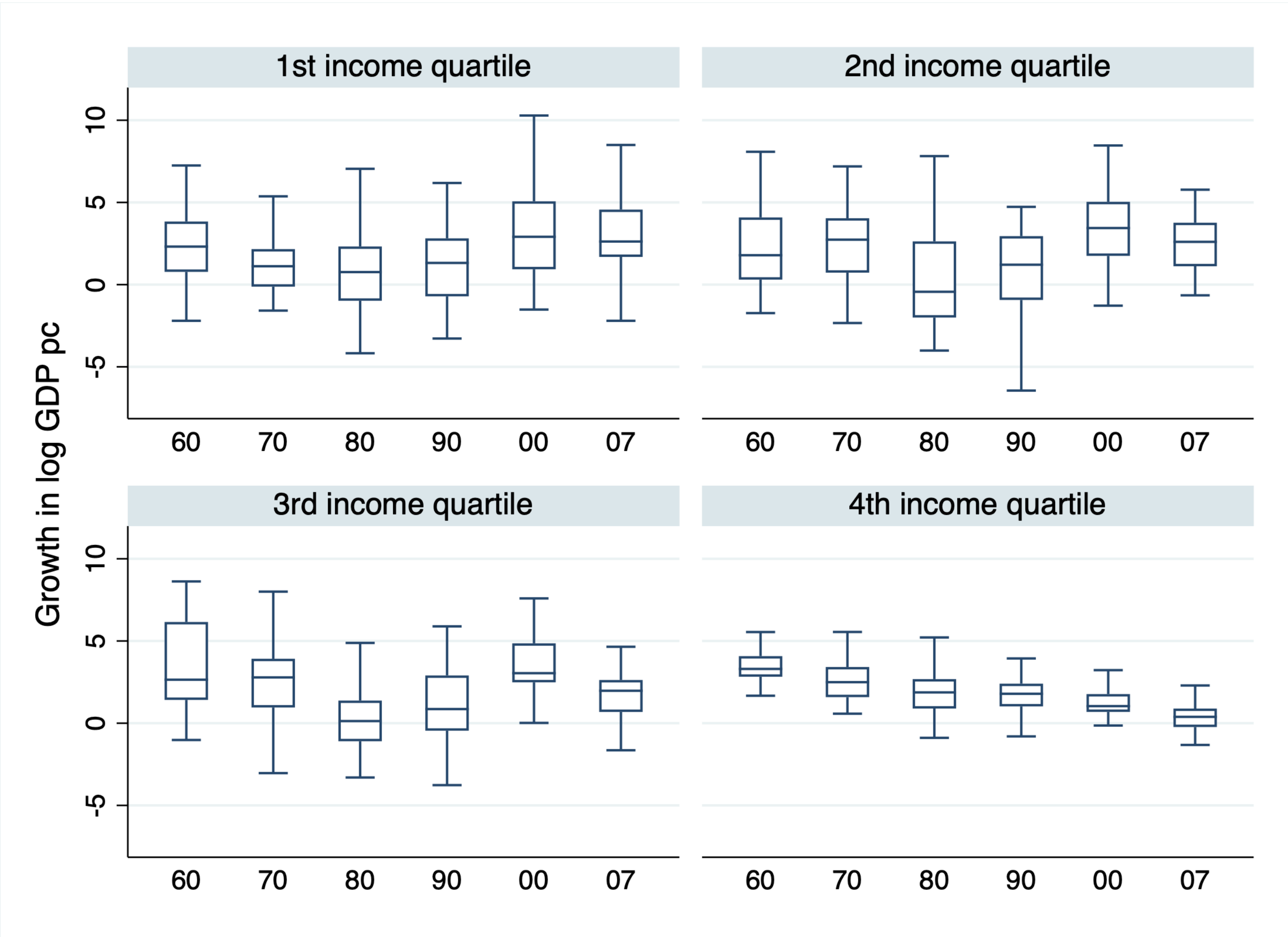
$$\pi_L = \frac{1}{\gamma\sigma_G^2}\frac{\sigma_G^2\tilde{\mu_L} - \rho\sigma_L\sigma_G\tilde{\mu_G}}{(1-\rho^2)\sigma_L^2 + p\sigma_b^2}$$

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

C Chapter 3 Appendix

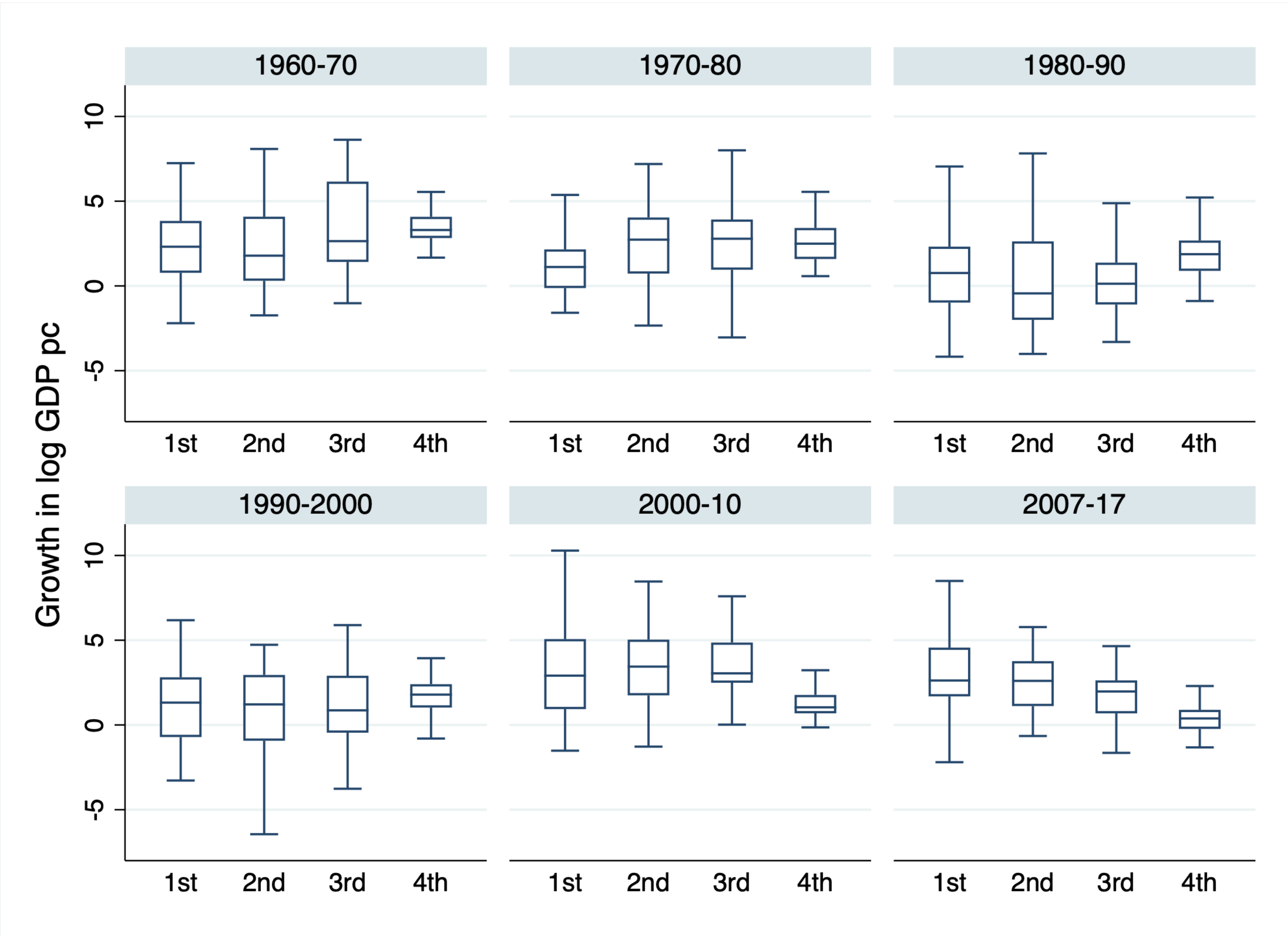
C.1 Income

Figure C.1: Trend in growth by income quartile, 1960-2007



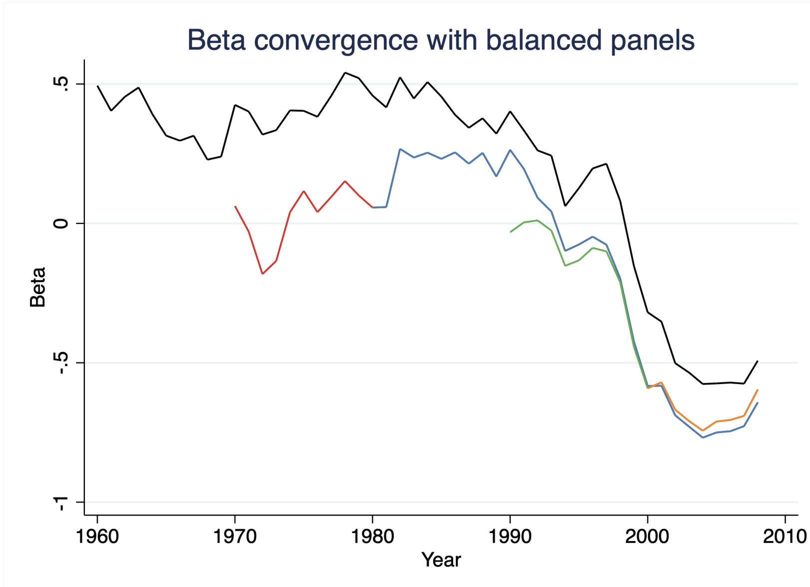
Notes: These are boxplots of country's average annual growth in GDP per capita, PPP, for a given decade. Each facet shows one quartile of countries, based on baseline GDP per capita that decade, with the 1st quartile being the lowest income and the fourth the highest. Within a facet, the plot shows how decade average growth for that quartile varied over time. The top of the box is the 75th percentile of average growth in that quartile, the center is the median (the 50th percentile), and the bottom is the 25th percentile.

Figure C.2: Boxplot of growth vs. country quintile, split by decade.

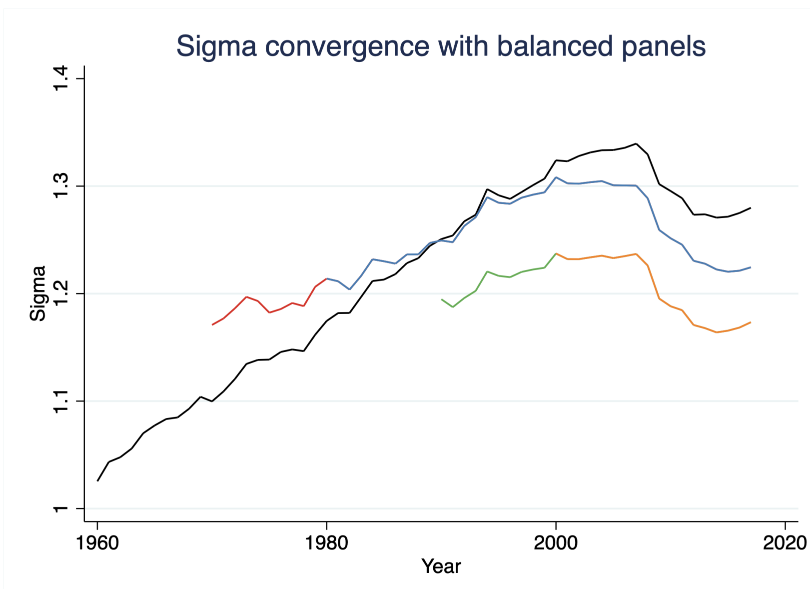


Notes: These are boxplots of country's average growth in GDP per capita for a decade. Each facet shows one decade. Within a facet, the plot shows how decade average growth varied by quartile of baseline GDP per capita. The top of the box is the 75th percentile of average growth in that quartile, the center is the median (teh 50th percentile), and the bottom is the 25th percentile. The whiskers represent the corresponding maximum and minimum. The last decade starts in 2007, since our data runs to 2017.

Figure C.3: Robustness of convergence to balanced panel.



(a) Robustness of $\beta-$convergence.



(b) Robustness of $\sigma-$convergence.

Notes: This figure shows robustness of the convergence coefficients to using balanced panels. Since countries are joining our dataset over time, we plot 5 different curves, one starting at the beginning of each decade. A given decades curve shows the evolution of the convergence coefficients going forward from the start of that decade, based upon the constant set of countries who were in the dataset at the start of that decade.

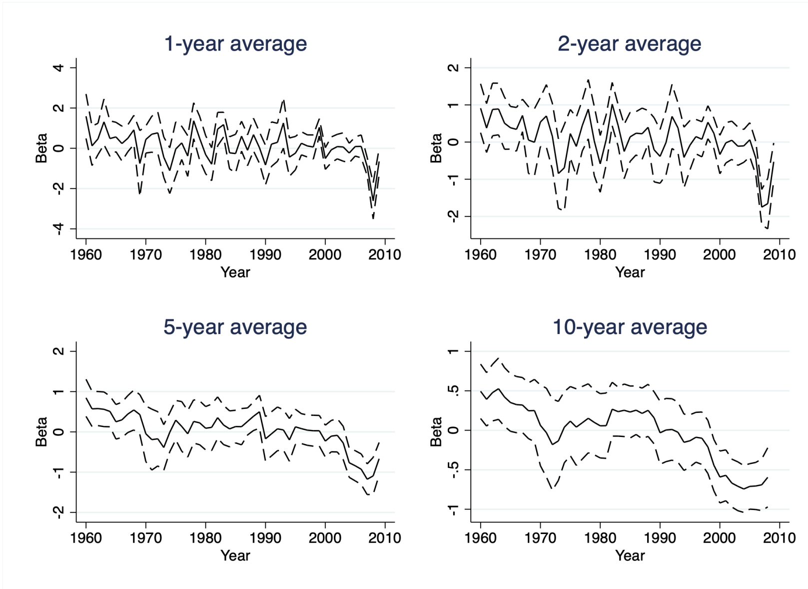


Figure C.4: Robustness of $\beta-$convergence to averaging period.

Notes: This figure shows robustness to the averaging period used for β-convergence. In particular, the plots show the β-convergence coefficients using subsequent 1, 2, 5, and 10 year average growth rates.

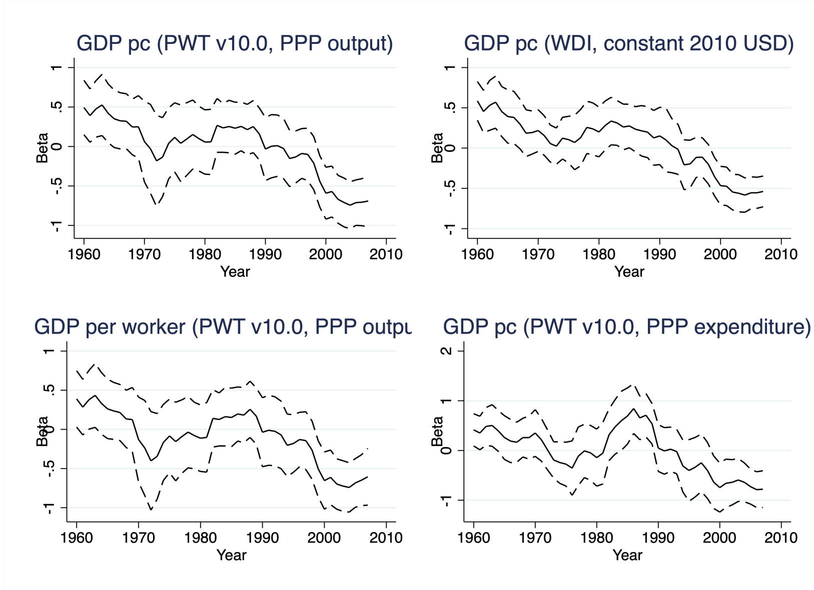


Figure C.5: Robustness of $\beta-$convergence to measure of output.

Notes: This figure shows robustness to the outcome used for β-convergence. Our baseline specification uses GPD pc in constant PPP output, from the PWT v10.0.

C.2 Correlates

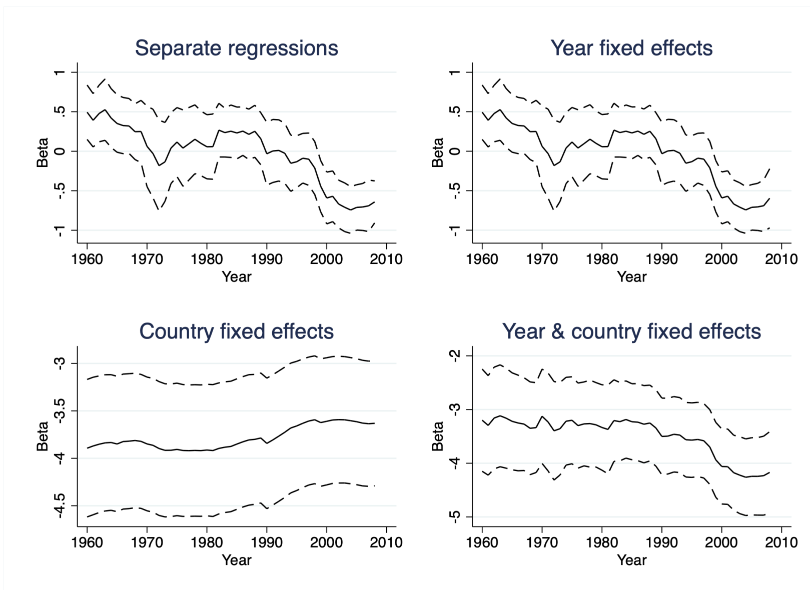


Figure C.6: $\beta-$convergence under alternative regression specifications.

Notes: This figure shows robustness to the specification used for β-convergence. The first specification uses separate regressions for each year, while others pool across years and cluster by country. The second specification includes year fixed effects(our baseline specification). The third specification includes country fixed effects. The fourth specification includes both country and year fixed effects.

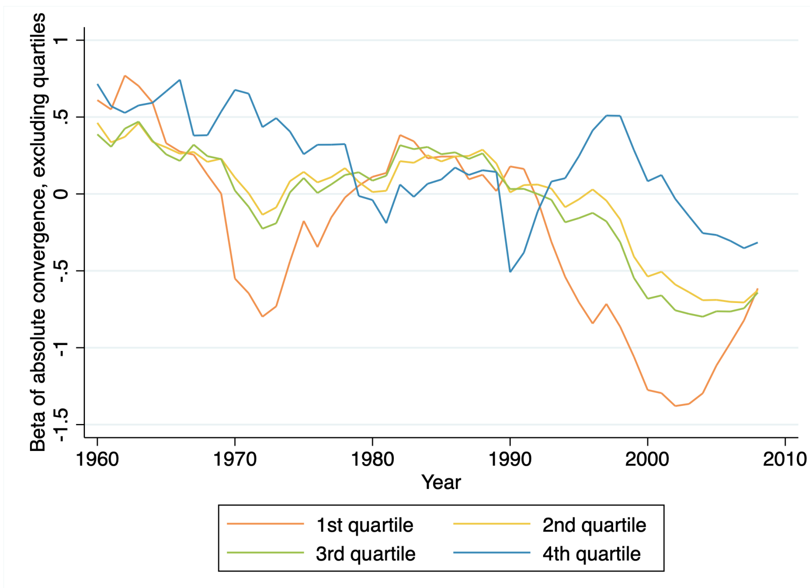


Figure C.7: Catch-up of the poor or slow-down of the rich? $\beta-$convergence when excluding countries from different quartiles of per capita income.

Notes: This figure reports the sensitivity of the absolute convergence coefficient β to excluding different quartiles of wealth from the sample. The legend refers to which wealth quartile is being dropped, where the 1st is the poorest.

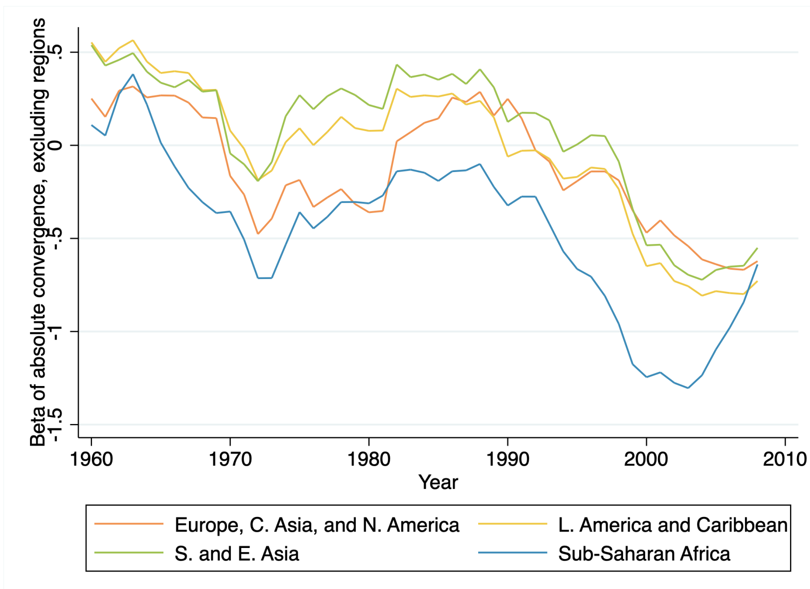


Figure C.8: Which regions are converging? $\beta-$convergence when excluding countries from different regions.

Notes: This figure reports the sensitivity of the absolute convergence coefficient β to excluding different regions. The legend refers to which region is being dropped.

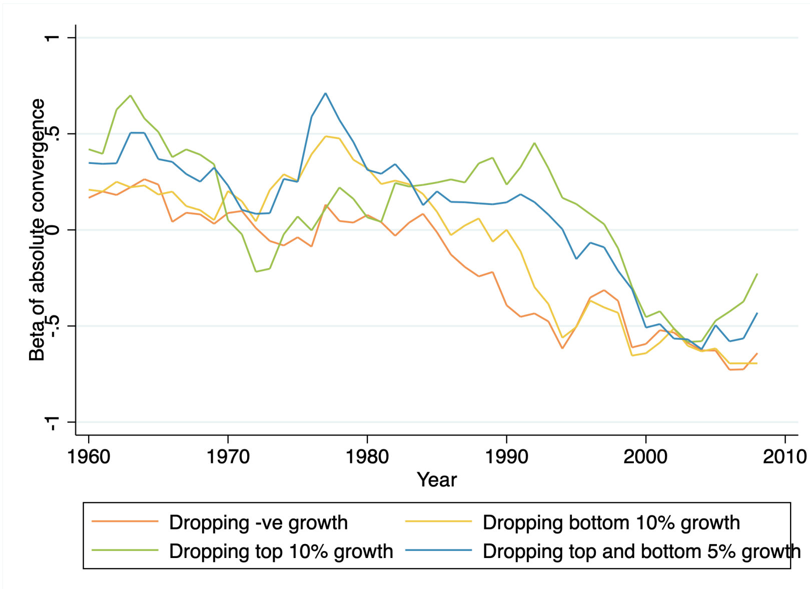
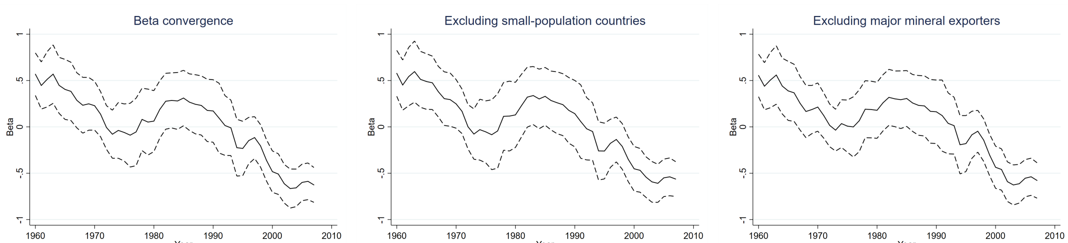


Figure C.9: Disasters, growth miracles, and stagnation. $\beta-$convergence when excluding outlying growth rates.

Notes: This figure reports the sensitivity of the absolute convergence coefficient β to excluding countries based on their subsequent 10-year growth (which is conditioning on an outcome variable, but useful for diagnostic purposes). The legend refers to which countries are being dropped.



(a) Main specification.

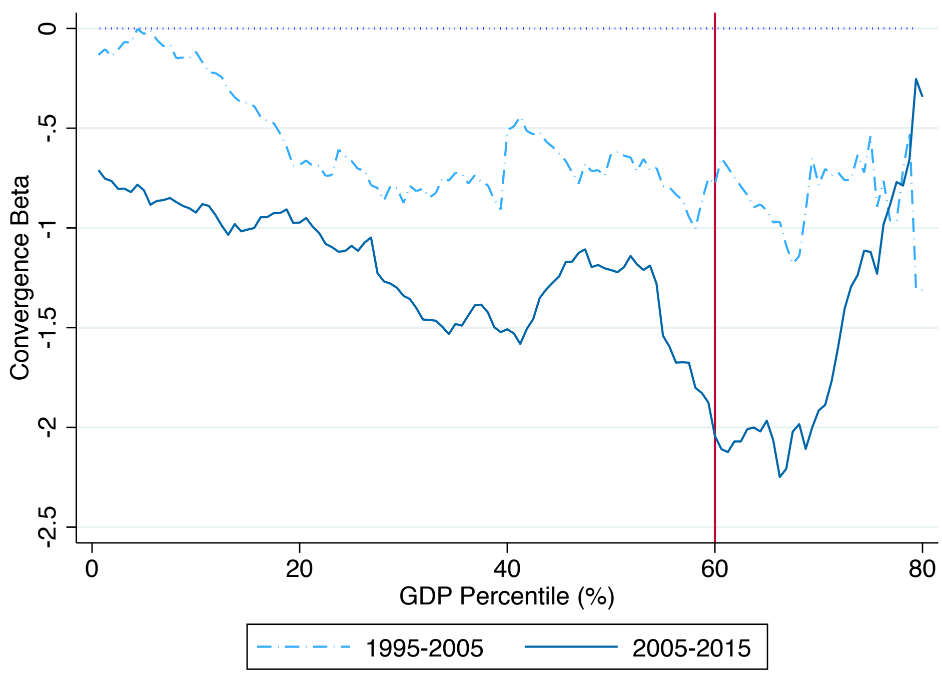
(b) Excluding small population countries.

(c) Excluding major mineral exporters.

Figure C.10: Robustness of $\beta-$convergence to excluding small countries and major mineral exporters.

Notes: These graphs show robustness of the β-convergence plot to natural changes in the set of countries. a) is the original, main specification. b) Excludes countries for whom exports of minerals accounted for > 20% of their GDP in 2010. c) Excludes countries whose population was less than 500,000 in 2010.

Panel A: Conditional convergence in decades from 1965 to 1995



Panel B: Conditional convergence in decades 1995 to 2005

Figure C.11: Club convergence by income

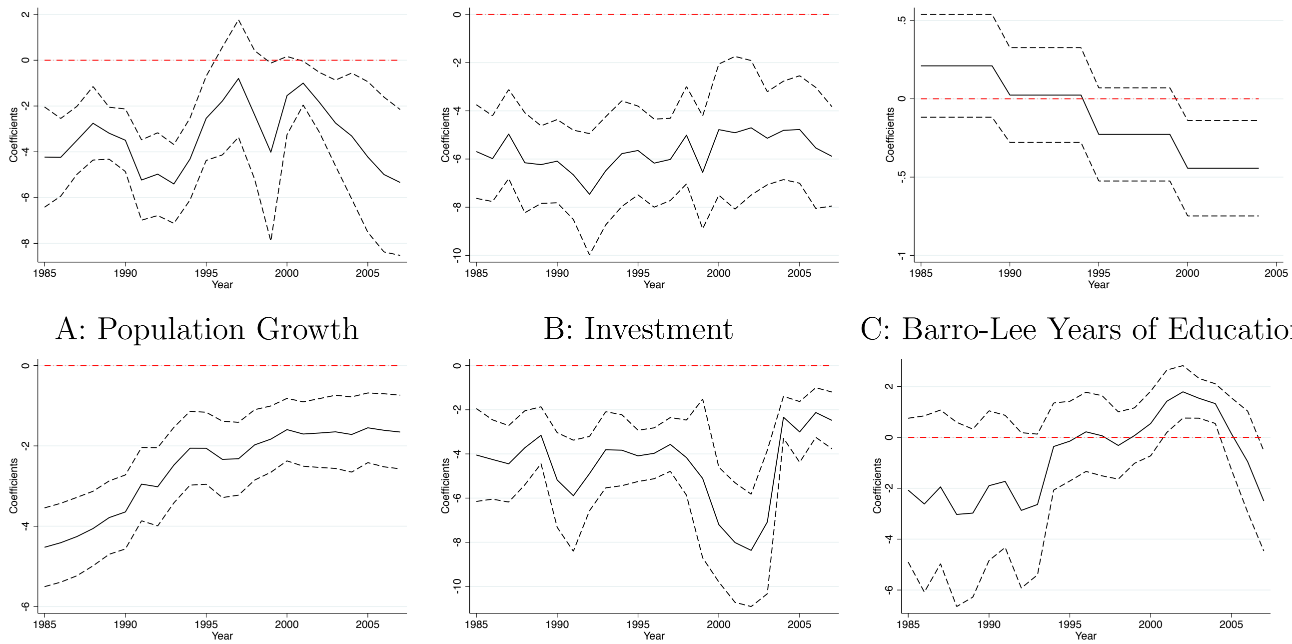
Notes: This figure plots β convergence conditional on the rank of GDP per capita ($> X\%$), from absolute convergence β ($X = 0$) to β conditional in top 20% income percentile ($X = 80$). Panel A reports the convergence β conditional on income for the three decades in the pre-convergence era: 1965-1975, 1975-1985, and 1985-1995. Panel B reports the β for the two decades in the post-convergence era: 1995-2005 and 2005-2015. The red vertical lines imply the cutoff for country sub-sample in the top 40% income percentile. The blue dotted lines are the benchmark of no convergence.

Table C.1: Convergence in culture using the World Value Surveys

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Trust	-0.00645									
	(0.00802)									
Perception on Inequality		-0.0265**								
		(0.0123)								
Politics - Respect for Authority			-0.0177**							
			(0.00828)							
Interest in Politics				-0.0269**						
				(0.0104)						
Political Actions					-0.0635***					
					(0.00900)					
Importance of Politics						-0.0184**				
						(0.00777)				
Importance of Family							-0.0435***			
							(0.00853)			
Work Ethics								-0.0329***		
								(0.0111)		
Religion									0.00376	
									(0.00475)	
Tradition										-0.0708***
										(0.0131)
Constant	0.0116	0.110	0.0287**	0.0804***	0.139***	0.0539**	0.0470***	0.0495***	-0.00431	0.0237***
	(0.0140)	(0.0733)	(0.0135)	(0.0281)	(0.0215)	(0.0214)	(0.00980)	(0.0161)	(0.0109)	(0.00851)
N	33	32	32	31	33	33	33	33	33	33

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

Notes: This table reports $\beta-$ convergence regressions, for country-level changes in cultural traits in the World Value Surveys (WVS). Country level traits are calculated as the population-weighted average of the traits reported in the WVS. The sample is countries which are surveyed both in wave 6 of the WVS (2010-2014) as well as in at least one of the waves 3-5 (1995-2009). To adjust for the different survey frequency, we take the annualized change. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



A: Population Growth B: Investment C: Barro-Lee Years of Education

D: Polity 2 E: Government spending F: Credit by Financial Sector

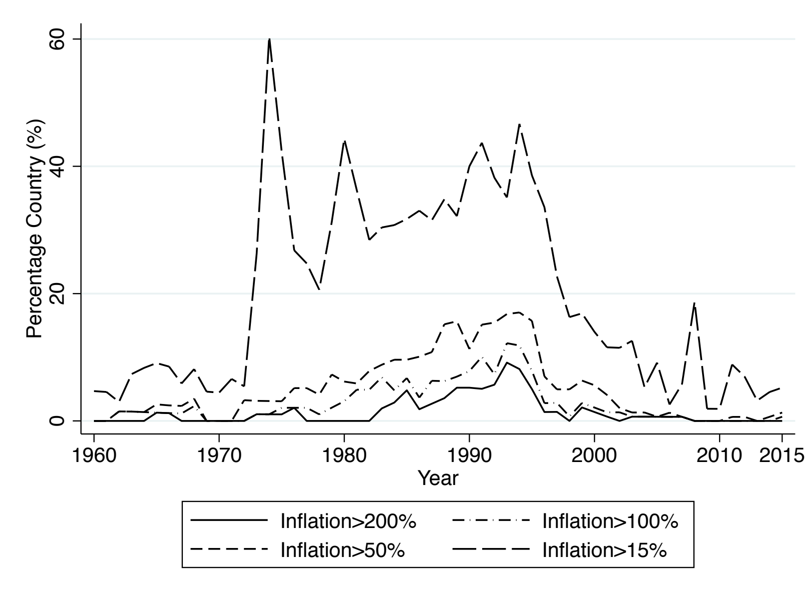
Figure C.12: Convergence in correlates of income and growth

Notes: This figure plots the correlate convergence β_t as a function of year t estimated from regressing the correlate change in the next decade (from year t to $t+10$) on the current correlate (in year t):

$$100\frac{Inst_{i,t+10} - Inst_{i,t}}{10} = \beta_t Inst_{t,i} + \mu_t + \epsilon_{t,i}$$

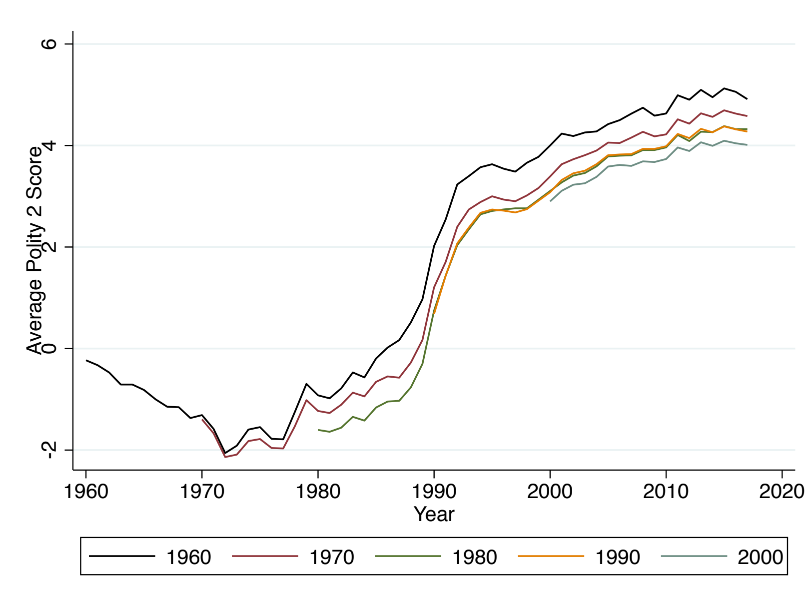
Five institutions are included: polity 2 score, rule of law (WGI), government spending (% GDP), credit provided by the financial sector, and Barro-Lee education attainment of age cohorts from 25 to 60. The dashed horizontal red lines are benchmark $\beta_t = 0$

Figure C.13: Hyper-inflation over time



Notes: This figure plots four series of the percentage of countries experience inflation above 200%, 100%, 50%, and 15%.

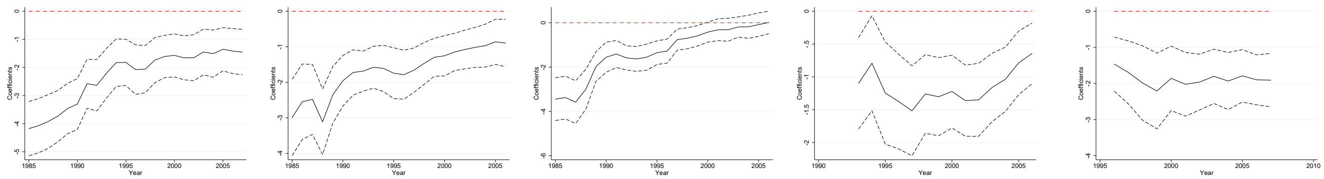
Figure C.14: Polity 2 score with fixed country samples



Notes: Average Polity 2 score with the country samples available in 1960, 1970, 1980, 1990, and 2000.

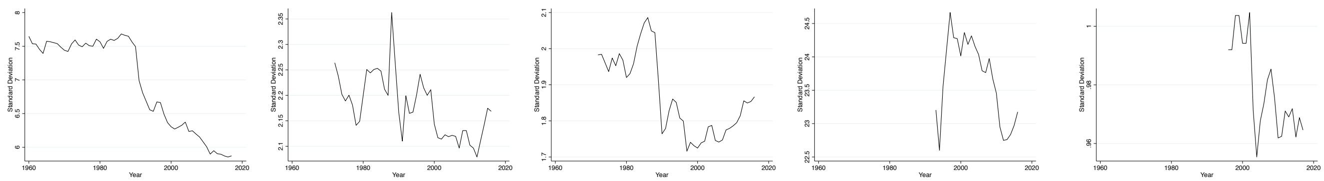
Figure C.15: Convergence in Political Institutions

Panel A: Beta-Convergence



Panel A1: Polity 2 | Panel B1: Political Rights | Panel C1: Civil Liberty | Panel D1: Media Freedom | Panel E1: WGI Political Stability

Panel B: Sigma-Convergence

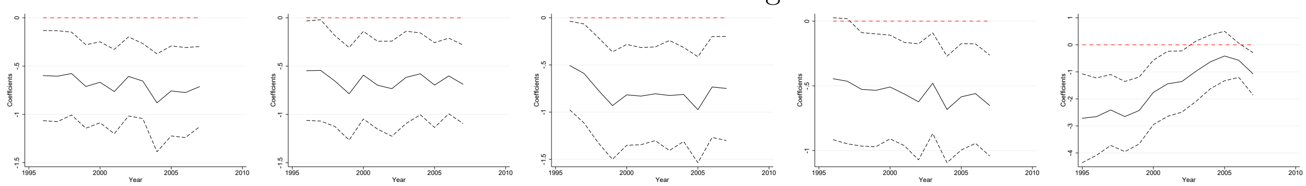


Panel B1: Polity 2 | Panel B2: Political Rights | Panel B3: Civil Liberty | Panel B4: Media Freedom | Panel B5: WGI Political Stability

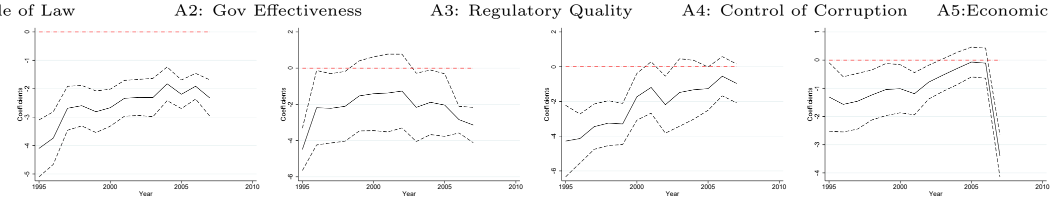
Notes: Political institution measures include Polity 2 score from Center of Systematic Peace (1960-2015), Freedom House political rights score (1973- 2015), Freedom House civil liberty score (1973-2015), Press Freedom score (1995-2015), and WGI political stability. The top panels (A1-A5) report results of Beta convergence. The bottom panels (B1-B5) report results of Sigma convergence.

Figure C.16: Convergence of Governance

Panel A: Beta-Convergence



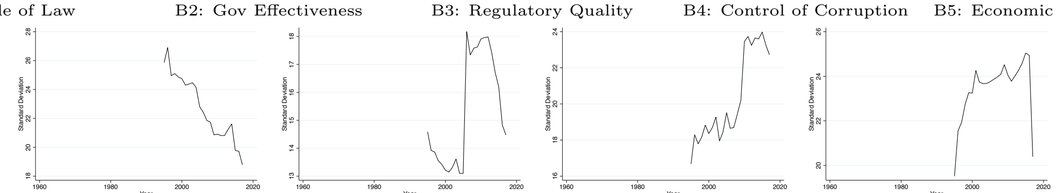
A1: Rule of Law A2: Gov Effectiveness A3: Regulatory Quality A4: Control of Corruption A5:Economic Freedom Score



A6: Government Integrity A7: Business Freedom A8: Investment Freedom A9: Property Rights

Panel B: Sigma-Convergence

B1: Rule of Law B2: Gov Effectiveness B3: Regulatory Quality B4: Control of Corruption B5: Economic Freedom Score

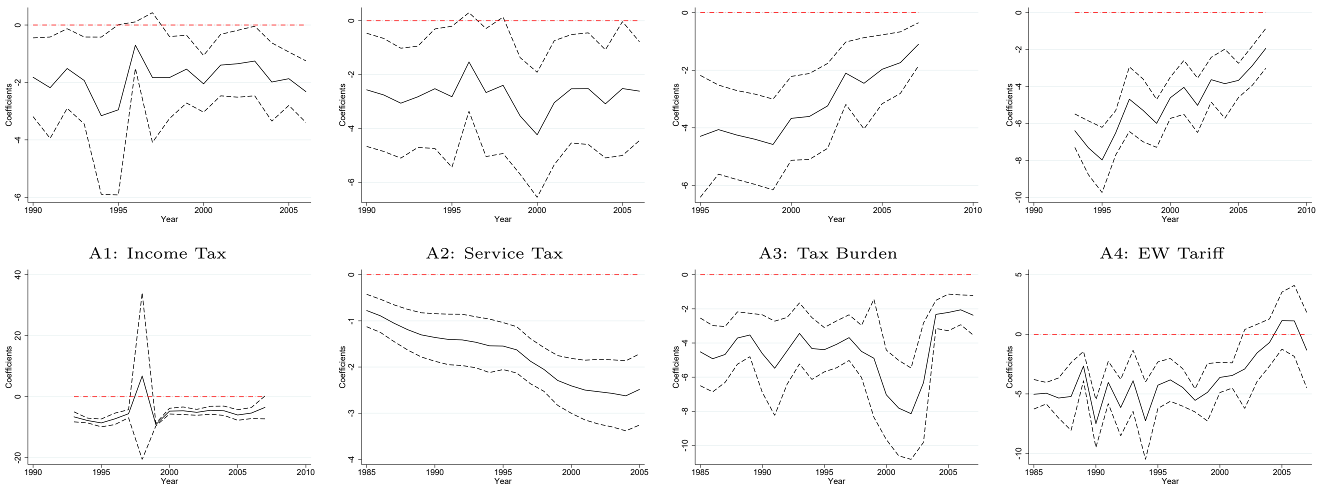


B6: Government Integrity B7: Business Freedom B8: Investment Freedom B9: Property Rights

Notes: Governance quality measures include rule of law, government effectiveness, regulatory quality, control of corruption, overall economic freedom score, government integrity, business freedom, investment freedom, and property rights. The top panels (A1-A9) report results of Beta convergence. The bottom panels (B1-B9) report results of Sigma convergence.

Figure C.17: Convergence in Fiscal Policy

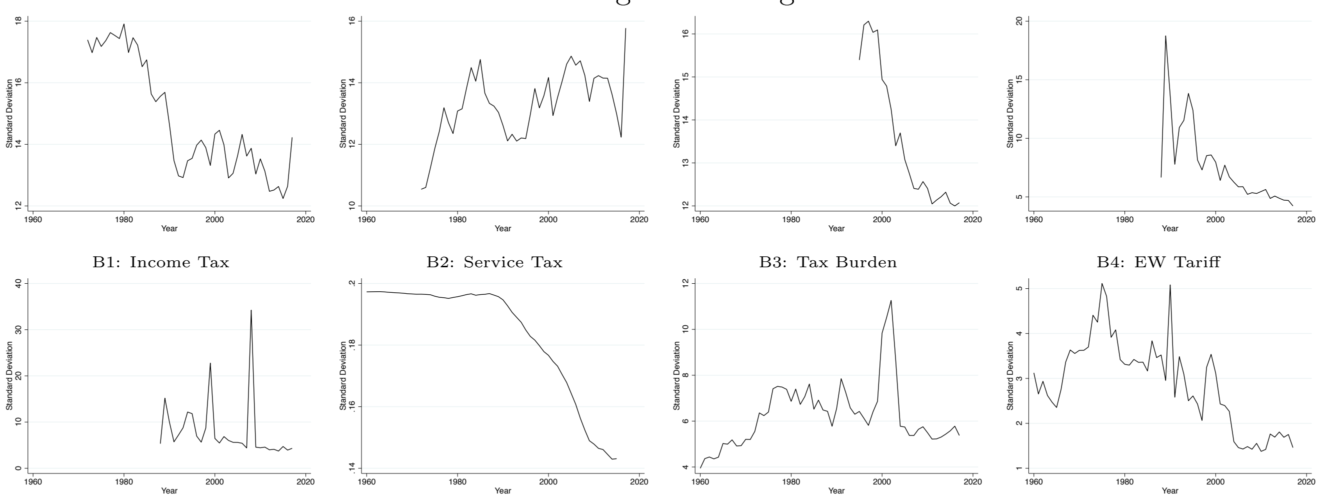
Panel A: Beta-Convergence



A1: Income Tax A2: Service Tax A3: Tax Burden A4: EW Tariff

A5: VW Tariff A6: Private Investment A7: Government Spending A8: Military Expenditure

Panel B: Sigma-Convergence



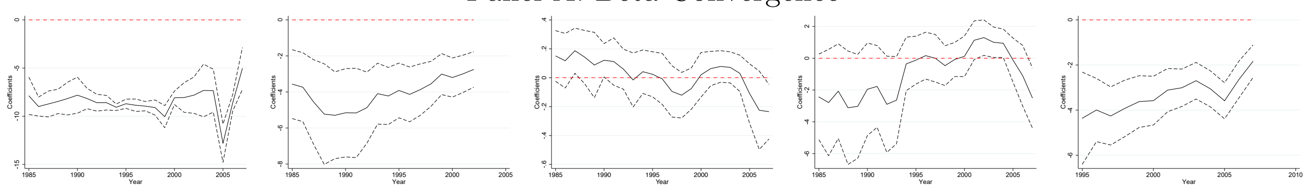
B1: Income Tax B2: Service Tax B3: Tax Burden B4: EW Tariff

B5: VW Tariff B6: Private Investment B7: Government Spending B8: Military Expenditure

Notes: Fiscal policy measures include tax on income and capital gain (% tax revenue),tax on goods and service (% tax revenue), tax burden score, equal-weighted tariff rate, value-weighted tariff rate, private investment (% total investment), government spending (% GDP), and military expenditure (% GDP). The tax burden is a quadratic decreasing function with of tax as a portion of GDP. See https://www.heritage.org/index/fiscal-freedom for more explanation. The top panels (A1-A8) report results of Beta convergence. The bottom panels (B1-B8) report results of Sigma convergence.

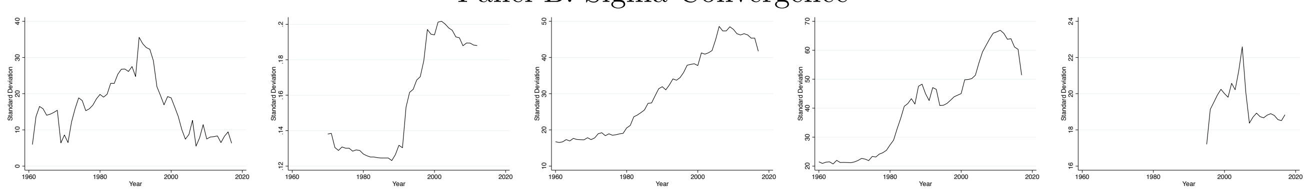
Figure C.18: Convergence in Financial Institutions

Panel A: Beta-Convergence



A1: Winsorized Inflation A2: CBI A3: Credit to Private Sector A4: Bank Credit A5: Financial Freedom

Panel B: Sigma-Convergence

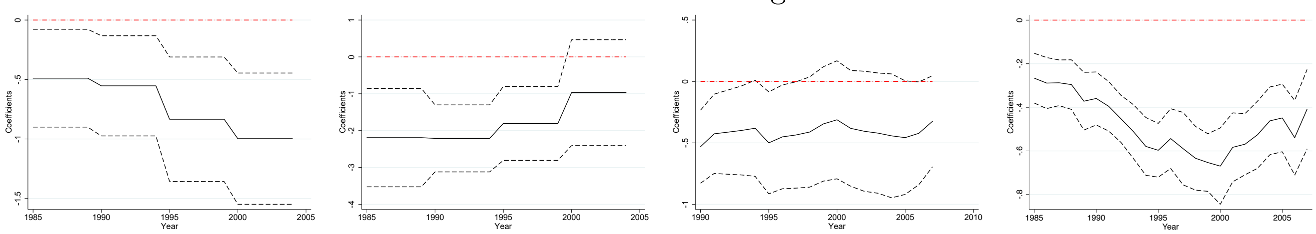


B1: Winsorized Inflation B2: CBI B3: Credit to Private Sector B4: Bank Credit B5: Financial Freedom

Notes: Financial institution measures include winsorized inflation, central bank independence, credit to private sector, credit by financial sector (bank credit), and financial freedom score. The annual inflation data is winsorized by 100% to reduce the impact of outliers. The top panels (A1-A5) report results of Beta convergence. The bottom panels (B1-B5) report results of Sigma convergence.

Figure C.19: Convergence in Labor

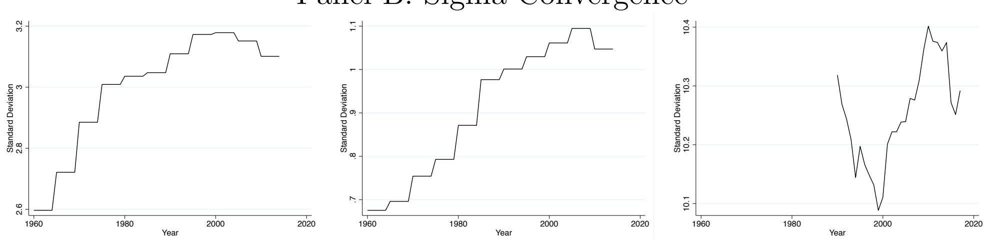
Panel A: Beta-Convergence



A1: Barro-Lee Age 25-29 A2: Education Gap by Gender A3: Labor Participation A4: Primary Enrollment

A5: Secondary Enrollment A6: Tertiary Enrollment

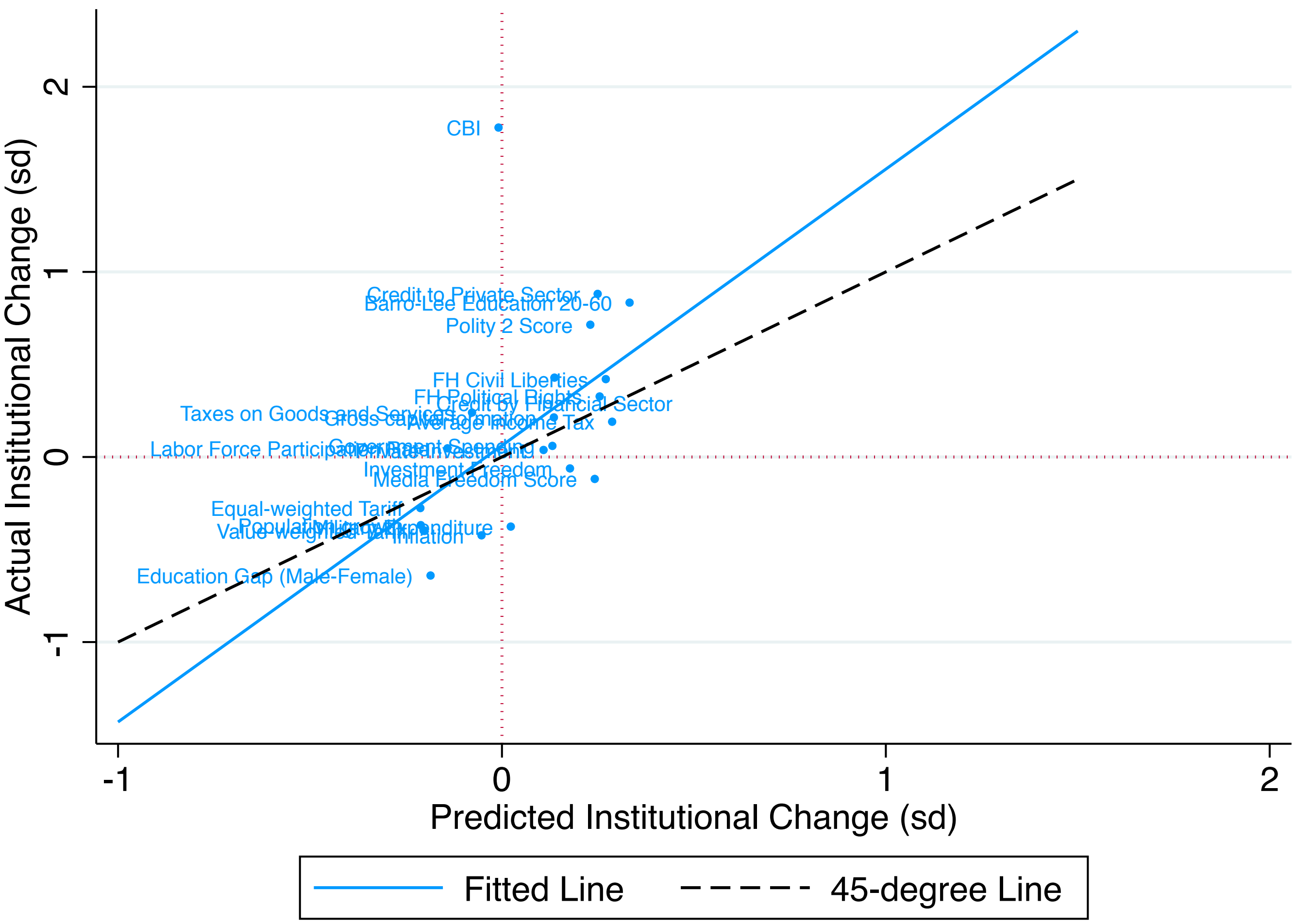
Panel B: Sigma-Convergence



B1: Barro-Lee Age 25-29 B2: Education Gap by Gender B3: Labor Participation

Notes: Labor measures include the quinquennial Barro-Lee educational attainment of Age group 25-29 (1970-2015), gender gap in educational attainment (male minus female), labor force participation rate, primary school enrollment rate, secondary school enrollment rate, tertiary school enrollment rate. The top panels (A1-A6) report results of Beta convergence. The bottom panels (B1-B6) report results of Sigma convergence.

Figure C.20: Actual and predicted change in correlates of income and growth from 1985 to 2015

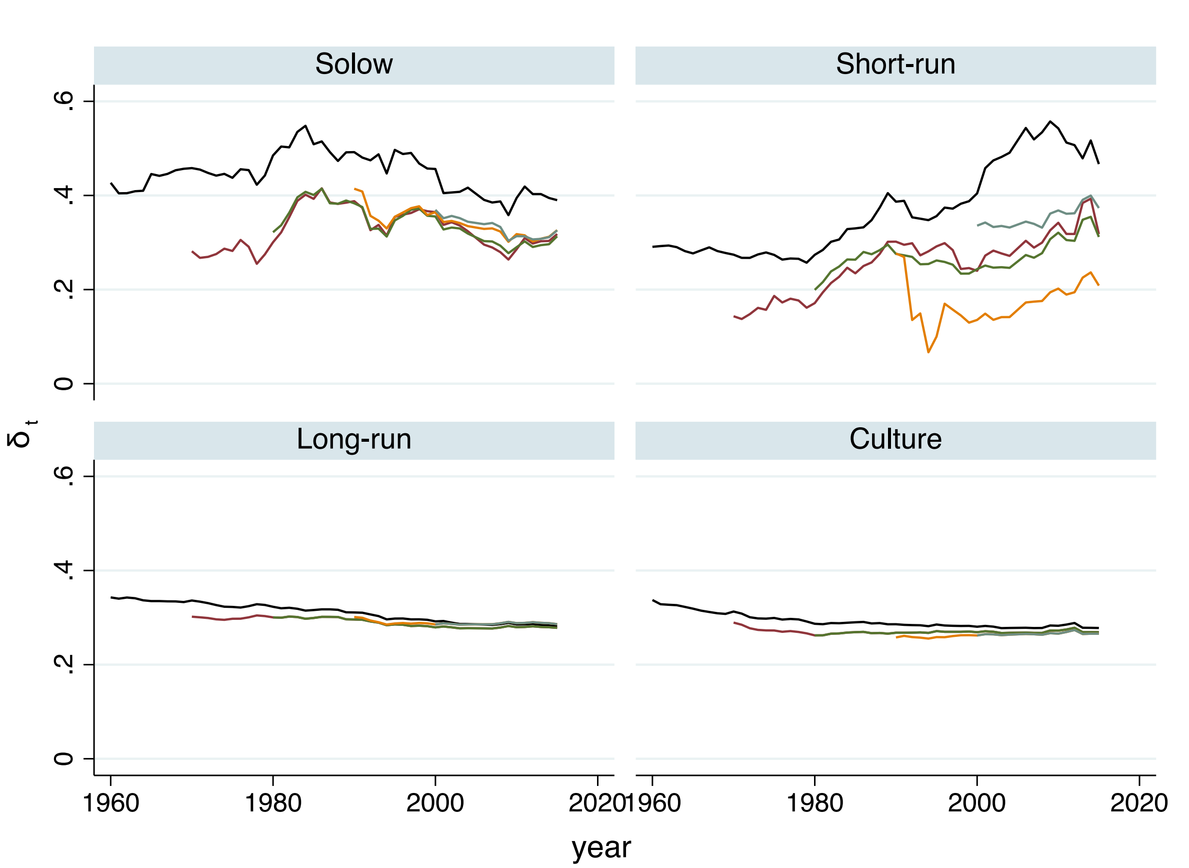


Notes: This figure plots the actual average correlate change from 1985 to 2015 versus the predicted average correlate change due to GDP growth, predicted using the GDP-correlate relationship in 1985 which is estimated by the following regression:

$$\frac{Inst_{i,1985}}{SD(Inst_{1985})} = \delta_{1985} log(GDPpc)_{i,1985} + \nu_{1985} + \epsilon_{i,1985}$$

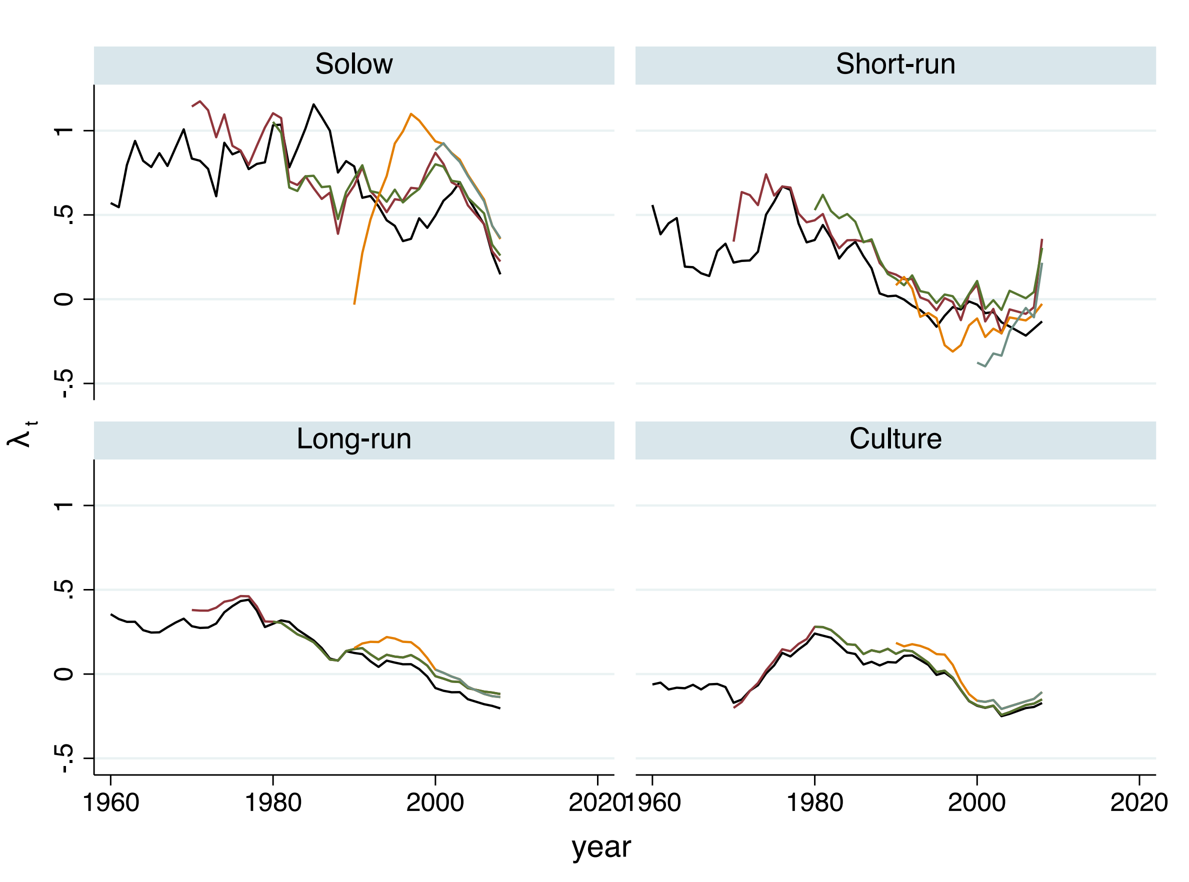
The predicted correlate change (on X-axis) is defined as $\delta_{1985}\text{mean}_i(log(GDPpc)_{i,2015} - log(GDPpc)_{i,1985})$. The actual correlate change (on Y-axis) is defined as $\text{mean}_i\left(\frac{Inst_{i,2015}-Inst_{i,1985}}{SD(Inst_{1985})}\right)$. The solid line is the fitted line of all correlates. The dashed line is the 45-degree degree line as a benchmark.

Figure C.21: Trend in correlate-income relationship (δ)



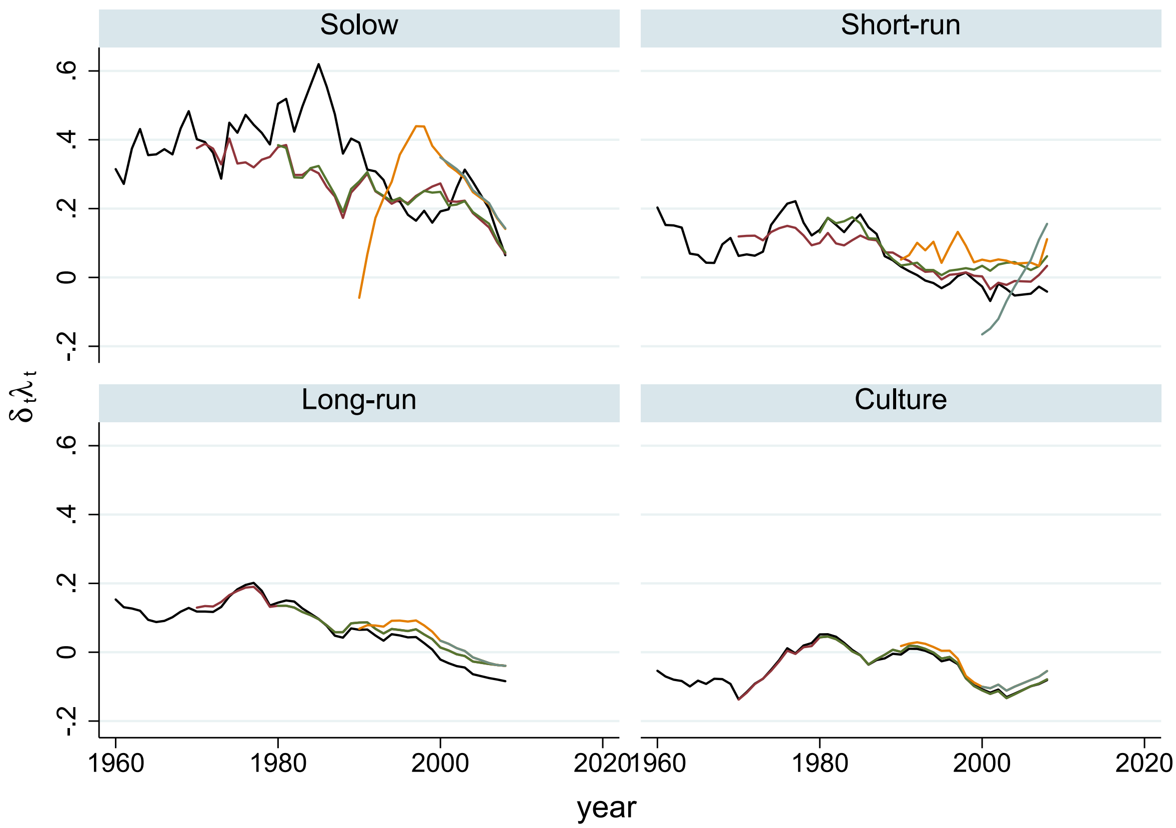
Notes: These figures plot δ_t - the slope of the correlate-income relationship - averaged across the different correlates. Each line represents a balanced panel, so that, for example, the line starting in 1960 is estimated from those country-correlate pairs for which data was available in 1960.

Figure C.22: Trend in growth-correlate relationship (λ)



Notes: These figures plot λ_t - the growth regression coefficient, controlling for baseline income - averaged across the different correlates. Each line represents a balanced panel, so that, for example, the line starting in 1960 is estimated from those country-correlate pairs for which data was available in 1960.

Figure C.23: Trend in difference between unconditional and conditional convergence, univariate ($\delta\lambda$)



Notes: These figures plot $\delta_t\lambda_t$ - the difference between unconditional and conditional convergence - averaged across the different correlates. Each line is estimated from balanced panels of correlate-country pairs, so that, for example, the line starting in 1960 is the average of those country-correlate coefficients for which data was available starting in 1960, and each country-correlate coefficient is estimated for the set of countries for which income data and that specific correlate were available in 1960.

Table C.2: Polity 2 Score Change by Decade

Decade	Increase in Polity 2	Decrease in Polity 2	Unchanged Polity 2	Obs
1960-1970	19.4%	30.1%	50.5%	103
1970-1980	23.8%	25.4%	50.8%	122
1980-1990	37.3%	9.7%	53.0%	134
1990-2000	52.9%	10.1%	37.0%	134
2000-2010	31.6%	13.3%	55.1%	158
2010-2015	19.3%	6.8%	73.9%	161

Notes: This table reports the portion of countries with an increase, decrease, and unchanged Polity 2 score for each decade: 1960-1970, 1970-1980, 1980-1990, 1990-2000, 2000-2010, and 2010-2015.

Table C.3: Democratization and Income by Decade

	(1)	(2)	(3)	(4)	(5)	(6)
	1960-1970	1970-1980	1980-1990	1990-2000	2000-2010	2010-2015
	Panel A: Dummy {Increase in Polity 2 Score}					
Log(GDP)	-0.403**	0.0575	0.0707	-0.468***	-0.137	-0.0173
	(-2.36)	(0.44)	(0.63)	(-3.99)	(-1.46)	(-0.18)
Obs	91	114	137	169	193	203
	Panel B: Dummy {Decrease in Polity 2 Score}					
Log(GDP)	-0.328*	-0.690***	-0.438*	-0.0895	-0.292*	-0.280
	(-1.68)	(-3.32)	(-1.81)	(-0.47)	(-1.79)	(-1.22)
Obs	68	96	114	127	154	158

Notes: This table reports the logit regressions of dummies of Polity 2 score increase or decrease on log(GDP). The dependent variable in Panel A is the indicator dummy of the increase in Polity 2 score, and the sample excludes the countries with perfect democracy (where the score increase is not possible). The dependent variable in Panel B is the indicator dummy of the decrease in Polity 2 score, and the sample excludes the countries with perfect dictatorship (where the score decrease is not possible). t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Correlate convergence: joint tests

	Chi-squared	P-value	Number of Institutions
	Panel A: 1996-2006		
Political Institution	155.10	1.09×10^{-31}	5
Governance Quality	317.97	0.00	9
Fiscal Policy	460.23	0.00	8
Financial Institution	122.43	9.61×10^{-25}	5
Labor	124.23	2.11×10^{-24}	6
	Panel B: 2006-2016		
Political Institution	98.29	1.21×10^{-19}	5
Governance Quality	207.81	0.00	9
Fiscal Policy	170.41.75	1.06×10^{-32}	8
Financial Institution	698.09	0.00	5
Labor	74.53	4.80×10^{-14}	6

Notes: This table reports the joint significance test for two decades 1996-2006 and 2006-2016. The null hypothesis is that correlate convergence does not exist in all Solow fundamentals and short-run correlates (all βs are zeros). 1996 is the first year, we have a full data for all institutional variables. Barro-Lee education and private investment are extended to 2016 with the latest value available in our data (2010 and 2014 respectively).

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