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Crypto, Corruption, and Capital Controls: Cross-Country Correlations

Marwa Alnasaa, Nikolay Gueorguiev, Jiro Honda, Eslem Imamoglu, Paolo Mauro, Keyra Primus, and Dmitriy Rozhkov

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ABSTRACT: Empirical investigation of the factors underlying the growing usage of crypto-assets is in its infancy, owing to data limitations. In this paper, we present a simple cross-country analysis drawing on recently released survey-based data. We explore the correlation of crypto-asset usage with indicators of corruption, capital controls, a history of high inflation, and other factors. We find that crypto-asset usage is significantly and positively associated with higher perception of corruption and more intensive capital controls. Notwithstanding the data limitations, the results support the case for regulating crypto-assets, including know-your-customer approaches, as opposed to taking a laissez-faire stance.

JEL Classification Numbers:	C21; G18; G28
Keywords:	cypto-assets, cryptocurrency, corruption, capital controls

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Introduction

The emergence of crypto-assets (private digital assets that depend primarily on cryptography and distributed ledger technology for record keeping) has unleashed a plethora of financial innovation that will likely revolutionize the form of money and the ways it is used.[1] These developments create opportunities as well as risks. As noted, for example, by a group of G-20 policymakers, "…technological innovation, including that underlying crypto-assets, has the potential to improve the efficiency and inclusiveness of the financial system and the economy more broadly," but "crypto-assets […] raise issues with respect to consumer and investor protection, market integrity, tax evasion, money laundering and terrorist financing."[2]

The pseudonymity of crypto-assets (whereby transactions require only digital identities) makes them a potential vehicle for illicit flows, including flows of proceeds from corruption. This pseudonymity is not an intrinsic feature of the underlying technology, but rather a choice made in the design and practice of most currently existing crypto-assets. Whereas cash provides full anonymity and large denomination bills have long been considered an aid for crime and tax evasion (Rogoff 2017, Chodorow-Reich et al. 2020), crypto-assets in their current form make it possible to move even larger amounts speedily and with greater ease, including across national borders (Graf von Luckner et al., 2021). As crypto-assets rapidly gain macroeconomic relevance (International Monetary Fund 2021) and policymakers consider the optimal degree of regulation, it is urgent to bring empirical evidence to bear on the question of whether crypto-assets facilitate corruption. Likewise, it is helpful to explore the extent to which crypto-assets are used to circumvent capital controls, for countries where these are in place, and whether crypto-assets are more likely to gain traction in countries where the local currency has historically not been a secure store of value.[3]

There are also potential benefits of the technologies that crypto-assets are based on. In particular, prudently designed central bank digital currencies could offer additional resilience, safety and availability with lower costs.[4] These technologies could also be used to improve transparency and record-keeping for procurement or other payments related to government projects, thereby increasing accountability, and reducing the scope for corruption. Likewise, property and registry systems could be enhanced, reducing red tape, and streamlining processes. However, these initiatives are currently less advanced or widespread than crypto-assets.[5]

Empirical investigation of the factors underlying the growing usage of crypto-assets is in its infancy, owing to data limitations. In this paper, we present a simple cross-country analysis drawing on recently released survey-based data. We explore the correlation of crypto-asset usage with indicators of corruption, capital

[1] Prasad (2021) provides an excellent comprehensive survey and analysis of how digitalization is transforming currencies and finance.

[2] Communiqué, G-20 finance ministers and central bank governors, March 20, 2018, Buenos Aires.

[3] Using individual-level data from the U.S. Survey of Consumer Payment Choice, Auer and Tercero-Lucas (2021) do not find evidence that crypto investors are motivated by distrust in fiat currencies.

[4] International Monetary Fund (2022) discusses the insights and policy lessons for central bank digital currencies.

[5] The important tradeoffs between costs (such as privacy) and benefits (such as financial inclusion) are discussed in Prasad (2021). Additional benefits of digitalization in government more generally are discussed in International Monetary Fund (2018).

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controls, a history of high inflation, and other factors. We find that crypto-asset usage is significantly and positively associated with corruption and capital controls. Whereas the small sample size and uncertain quality of the data on crypto-assets implies that our results must be interpreted with caution, it is also worth recalling that measurement error tends to reduce the likelihood of finding a significant empirical association; significant results with low-quality data are thus worth paying attention to. With these caveats in mind and considering the urgency of acting before it is too late, rather than waiting for conclusive evidence, we believe that, on balance, our results add to the case for regulating crypto-assets, including know-your-customer approaches, as opposed to taking a laissez-faire stance.

Data Description and Methodology

Our baseline data on crypto-currency usage are drawn from *Statista*, who collected them as part of their Global Consumer Survey. There were 2,000–12,000 respondents per country, with 55 countries covered (we are not able to confirm whether the respondents are representative of the whole population). The variable refers to the share of respondents who indicated they either owned or used cryptocurrencies in 2020, the year when the survey was conducted. Given the skewed distribution of the variable, to reduce the influence of a few countries with large shares of crypto use, in the analysis we use the logarithm of one plus the share of users in total population.

We are aware of four other data sources, which, however, suffer from methodological drawbacks. The 2021 Geography of Cryptocurrency Report by Chainalysis provides a *Global Crypto Adoption Index* covering July 2020-June 2021, constructed using a somewhat complicated formula.[6] As this index relies on web traffic data, it is likely to be distorted by the usage of VPNs and other products masking the geographic origin of online activity. Although the index covers 154 countries, more than half of the observations are close to zero, with several influential observations in the right tail of a highly skewed distribution (Appendix I). For the sake of completeness and transparency, we repeated our estimation using the Chainalysis data and report the results in Appendix I, but we consider these less reliable. A second alternative dataset, from Finder, is based on surveys with an even larger sample of participants per country, but it only covers 27 countries, which would yield insufficient degrees of freedom in the regressions. The third and fourth alternative datasets—*Global crypto adoption* (Triple A) and *Coin Dance*—suffer from even more serious shortfalls (e.g., the application of underlying assumption based only on Canada's case and covering only bitcoin volume). We did not conduct regression estimation using these last three data sources. As we report in the appendix, these various datasets do not provide a consistent picture, as the rankings they provide are weakly or not at all correlated.

The list of potential explanatory variables (for 2020, unless otherwise indicated) reflects the main possible incentives to crypto-asset use, with the control variable (secure internet servers) used to reflect the ability to engage in crypto-asset transactions. The variables include the following:

- *Control of corruption index*, from the Worldwide Governance Indicators.[7] The index ranges from -2.5 to 2.5 and consists of an aggregate indicator that combines the views of many enterprises, citizen

[6] The index comprises three metrics: 1) on-chain cryptocurrency received, 2) on-chain retail value received, and 3) peer-to-peer exchange trade volume. All three metrics are weighted by PPP based GDP per capita. The third metric is also weighted by number of internet users.

[7] A full data description is available at http://info.worldbank.org/governance/wgi/.

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and expert survey respondents in industrial and developing countries. It is based on over 30 individual data sources produced by a variety of survey institutes, think tanks, non-governmental organizations, international organizations, and private sector firms.[8]

- *Average consumer price inflation rate for 2011-20*, from the IMF's *World Economic Outlook*. A history of high inflation may make the domestic currency less attractive as a store of value. Past inflation is used as a proxy for the stability of the currency, which may affect the attractiveness of crypto assets as an alternative store of value. To reduce the weight of influential observations, the following logarithmic transformation is applied: log (1+inflation rate).
- *Capital openness.* Researchers have argued that crypto-assets may be used to circumvent capital controls.[9] We use the overall capital account openness index (also known as the Chinn-Ito Index) derived using the methodology developed in Chinn and Ito (2008). It combines several binary variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).[10] In our cross-country sample, the index ranges between -1.9 and 2.3, with higher values representing greater financial openness. We use the latest available value of this index, which is for 2019.
- *Logarithm of real GDP per capita in PPP terms*, as a general proxy for economic development.
- *Average Remittances for 2017-19.* Personal remittances received in percent of GDP. Data for 2020 are not included to avoid the effects of the COVID-19 pandemic shock.
- *Commercial bank branches* per 100,000 adults, from IMF's Financial Access Survey, is used as a proxy for domestic financial development and financial inclusion. Residents of countries where the traditional financial sector is well developed may be less likely to feel the need for crypto-assets.[11] We use the logarithm of this variable.
- *Secure internet servers,* measured per 1 million people from World Bank's population estimates. It is used as a control for internet penetration and digitalization of the economy. We expect this variable to be positively correlated with crypto-asset use as digital connectivity is needed for crypto transactions. We use the logarithm of this variable.

Descriptive statistics of all variables are provided in Table 1. Scatter plots and a simple pairwise correlation matrix show that crypto-asset usage is significantly associated with each of the potential explanatory variables (Figure 1). As a robustness check, all simple correlations remain significant when we remove significant outliers. In view of the high correlations among explanatory variables, multicollinearity is a methodological challenge (Table 2). Specifically, relatively high correlations are present between control of corruption indicators and real GDP per capita and capital controls.

[8] The results are essentially identical (not shown for brevity) using the corruption perceptions index by Transparency International, which correlates strongly (0.99) with the control of corruption index from WGI. Although these measures of corruption are largely based on perceptions, they are unlikely to have been affected by crypto usage, because cross-country corruption rankings have been fairly stable for many years, and crypto adoption is a recent phenomenon.

[9] For example, Graf von Luckner et al. (2021) conclude that "the notion that the use of crypto currencies is changing the economics of capital control evasion, and that, in turn, capital control evasion is an important driver for the expansion of crypto markets is broadly in line" with the case study they present.

[10] Details can be found in Chinn and Ito (2008).

[11] Survey-based measures of financial access would also be worth exploring but would curtail the size of the sample.

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Figure 1. Crypto-Asset Adoption and Potential Explanatory Factors (continued)

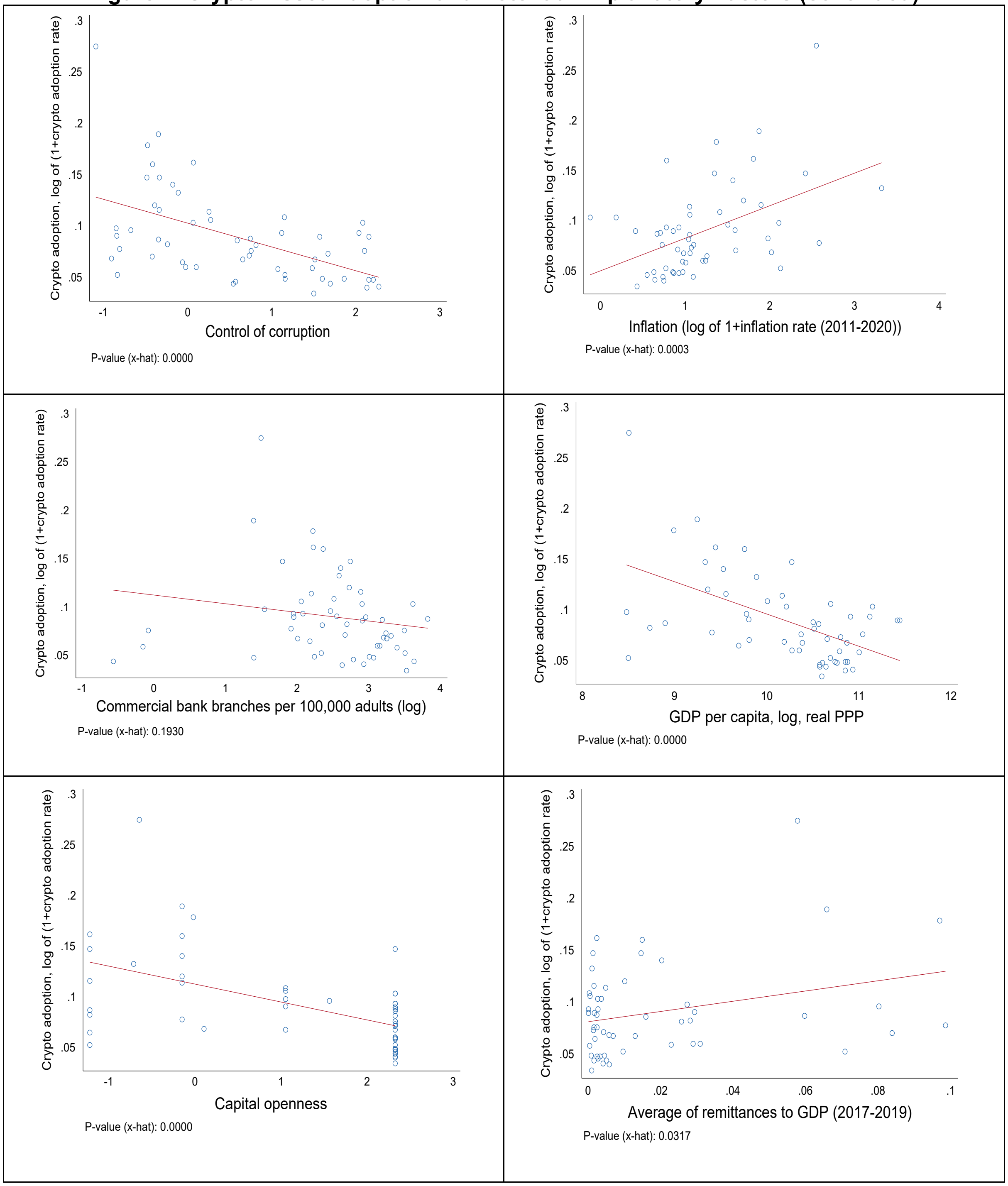

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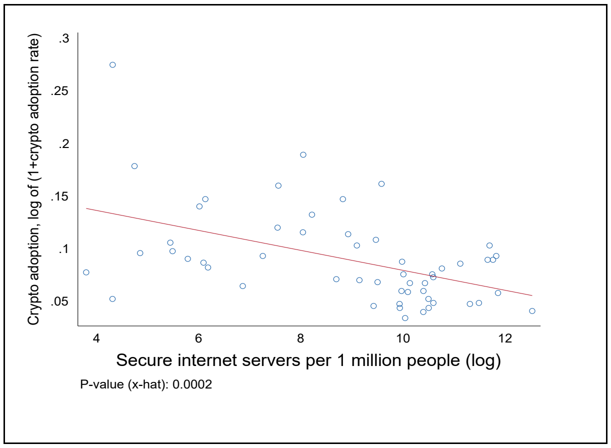
Figure 1. Crypto-Asset Adoption and Potential Explanatory Factors (concluded)



Source: Statista, Worldwide Governance Indicators, IMF World Economic Outlook, IMF Global Debt Database, IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER), IMF Financial Access Survey, World Bank Population Estimates, IMF Staff Calculations.

Table 1. Descriptive Statistics

Variables	Mean	Median	Std. dev.	Min	Max
Crypto adoption (log of (1+crypto adoption rate))	0.093	0.084	0.045	0.036	0.277
Control of corruption (index)	0.579	0.566	1.031	-1.097	2.270
Inflation (log of 1+inflation rate (2011-2020))	1.217	1.050	0.650	-0.124	3.317
Real GDP per capita (log, PPP 2017, international dollars)	10.196	10.386	0.775	8.475	11.445
Capital openness (index)	1.239	2.322	1.386	-1.226	2.322
Commercial bank branches (log, per 100,000 adults)	2.462	2.603	0.906	-0.570	3.818
Average of remittances to GDP (2017-2019)	0.017	0.004	0.025	0.000	0.098
Secure internet servers (log, per 1 million people)	8.870	9.576	2.348	3.784	12.532

Note: Descriptive statistics are for the 53 countries in the regression sample. These countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Dominican Republic, Egypt, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Arab Emirates, United Kingdom, United States, and Vietnam.

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Table 2. Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Crypto adoption (log of (1+crypto adoption rate))	1.00							
(2) Control of corruption (index)	-0.53*** (0.00)	1.00						
(3) Inflation (log of 1+inflation rate (2011-2020))	0.47*** (0.00)	-0.47*** (0.00)	1.00					
(4) Real GDP per capita (log, PPP 2017, international dollars)	-0.54*** (0.00)	0.71*** (0.00)	-0.39*** (0.00)	1.00				
(5) Capital openness (index)	-0.54*** (0.00)	0.55*** (0.00)	-0.34*** (0.00)	0.57*** (0.00)	1.00			
(6) Commercial bank branches (log, per 100,000 adults)	-0.18 (0.19)	0.29*** (0.00)	-0.36*** (0.00)	0.45*** (0.00)	0.25*** (0.00)	1.00		
(7) Average of remittances to GDP (2017-2019)	0.29** (0.03)	-0.31*** (0.00)	0.10 (0.18)	-0.36*** (0.00)	-0.18** (0.02)	0.05 (0.55)	1.00	
(8) Secure internet servers (log, per 1 million people)	-0.49*** (0.00)	0.74*** (0.00)	-0.34*** (0.00)	0.85*** (0.00)	0.53*** (0.00)	0.46*** (0.00)	-0.25*** (0.00)	1.00

Note: p-values are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Multivariate Regressions (general-to-specific) with Crypto Adoption as Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Control of corruption (index)	-0.015 (-1.384)	-0.014 (-1.406)	-0.014 (-1.422)	-0.013 (-1.644)	-0.015** (-2.142)	-0.014* (-1.984)
Capital openness (index)	-0.009 (-1.184)	-0.009 (-1.425)	-0.009 (-1.560)	-0.009 (-1.580)	-0.009* (-1.885)	-0.011* (-2.008)
Commercial bank branches (log, per 100,000 adults)	-0.009 (-1.424)	-0.009 (-1.411)	-0.009 (-1.433)	-0.009 (-1.496)	-0.009 (-1.473)	
Real GDP per capita, (log, PPP 2017, international dollars)	-0.006 (-0.362)	-0.006 (-0.363)	-0.006 (-0.348)	-0.004 (-0.261)		
Secure internet servers (log, per 1 million people)	0.001 (0.233)	0.001 (0.236)	0.001 (0.267)			
Average of remittances to GDP (2017-2019)	-0.026 (-0.073)	-0.026 (-0.074)				
Inflation (log of 1+inflation rate (2011-2020))	-0.000 (-0.019)					
Constant	0.189 (1.107)	0.189 (1.087)	0.183 (1.096)	0.177 (1.051)	0.136*** (6.451)	0.114*** (11.333)
Observations	53	53	53	53	53	53
R-squared	0.377	0.377	0.376	0.376	0.374	0.340

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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Results

Turning to multivariate regression analysis, given the strong multicollinearity, the general-to-specific testing approach pioneered by Hendry (1995) and explained in detail in Hoover and Perez (2004)[12] was used to exclude potentially redundant variables. The Variance Inflation Factor (VIF) analysis confirms that multicollinearity is present, and this implies the need to ascertain which variable(s) among the multicollinear ones carry the primary correlation with the dependent variable.[13]

We ran several multivariate regressions, starting with all potential explanatory variables, and sequentially dropping the least significant ones (Table 3). At each stage, we used the standard F-test for the exclusion of the least significant variable, to confirm that the variable can be excluded without biasing the regression. We also performed the F-tests to confirm the redundancy of various combinations of these variables. Control of corruption and capital controls survive the elimination of the least significant variables.[14] At the last stage, it was not possible to distinguish between these two in terms of the level of significance, and neither was redundant. This leaves the following OLS regression (with robust standard errors):

$$\boldsymbol{y_i = \alpha + \beta_1 c_i + \beta_2 k_i + \varepsilon_i}$$

where y is crypto adoption, c is the control of corruption, k is the capital openness, α is the constant, β is the coefficient of interest (regression 6 in Table 3).

In this last regression, the p-values for the coefficients on control of corruption and capital account openness are 0.053 and 0.05, respectively. Countries with weaker control of corruption (more corruption) and lower degree of capital openness (more capital controls) tend to have a larger share of crypto adoption, suggesting that crypto assets may be used to transfer corruption proceeds or circumvent capital controls. A move from the 25th percentile to the 75th percentile in control of corruption and capital openness (other things being equal) is associated with a decline in crypto adoption by around 2 and 4 percentage points, respectively.

[12] Hoover and Perez (2004) use a Monte Carlo experiment to re-examine studies of cross-country growth regressions by Levine and Renelt (1992) and Sala-i-Martin (1997). They show that the cross-sectional version of the general-to-specific search methodology (sequentially eliminating the redundant variables, starting with the least significant) has a near nominal size and high power, an advantage compared to other methodologies. We did not undertake the extreme bounds tests à la Levine and Renelt (1992) or the modification of Sala-i-Martin (1997), because Hoover and Perez show that the former tests are too strict (exclude many valid variables), while the latter are too lax (include many irrelevant variables).

[13] The VIF is a measure of collinearity among explanatory variables in a regression. VIF value of an explanatory variable is a function of R2 from regressing that variable on the other explanatory variables. Generally, a VIF value above 4 is considered to indicate the presence of significant multicollinearity. The variables in this regression have an average VIF of 3.74, with GDP and control of corruption having VIFs above 4.

[14] The F-statistics for the joint elimination of the other three explanatory variables (GDP, inflation, and private sector credit) is 0.22, corresponding to a p-value of 0.88.

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Among other explanatory variables, the number of bank branches per capita is the last to be dropped and has consistently the expected sign (countries with more developed financial systems may be less inclined to use crypto assets) but is not statistically significant.

These findings are robust to alternative measures of the explanatory variables.[15] They are also not affected by removing potentially influential observations from regressions, like significant outliers in crypto usage and average inflation. The regression results are also still significant, when an alternative definition for crypto adoption is used, although that alternative definition suffers from significant deficiencies that make inference unreliable, key among which is deficiencies in ability to confidently assign adoption to countries (Appendix I).

Conclusion

Cross-country regression analysis using a general-to-specific approach finds that more crypto usage is empirically associated with higher perceived corruption and more intensive capital controls. Overall, our interpretation, combined with a principle of prudence given the rapid increase in macroeconomic relevance of crypto assets, is that this evidence adds to the case for regulating crypto usage—for example, by requiring intermediaries to implement know-your-customer procedures. The analysis also shows the need for better data to understand the dynamics and the key driving factors behind crypto adoption. Meanwhile, work should continue in using the technologies underlying crypto assets to realize the potential benefits to financial inclusion and the efficiency of governments.

[15] Using alternative variables, the Corruption Perceptions Index from Transparency International and Capital Control Measures index from Fernandez et al., has not changed our findings.

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References

Auer, Raphael, and David Tercero-Lucas, 2021, “Distrust or Speculation? The Socioeconomic Drivers of U.S. Cryptocurrency Investments,” BIS Working Paper No. 951, Bank for International Settlements.

Chinn, Menzie, and Hiro Ito, "A New Measure of Financial Openness", *Journal of Comparative Policy Analysis*, Volume 10, Issue 3 September 2008, p. 309 - 322.

Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayan, 2020, “Cash and the Economy: Evidence from India’s Demonetization,” *Quarterly Journal of Economics*, 57–103.

Graf von Luckner, Clemens, Carmen M. Reinhart, and Kenneth S. Rogoff, 2021, “Decrypting New Age International Capital Flows,” NBER Working Paper 29337.

Hendry, David F., 1995, *Dynamic Econometrics*, Oxford University Press.

Hoover, Kevin, and Stephen Perez, 2004, “Truth and Robustness in Cross-Country Growth Regressions”, *Oxford Bulletin of Economics and Statistics*, 66(5), 765-798.

International Monetary Fund, 2018, “Digital Government,” Chapter 2, *Fiscal Monitor*, October.

International Monetary Fund, 2022, “Behind the Scenes of Central Bank Digital Currency: Emerging Trends, Insights and Policy Lessons”, *IMF Fintech Note* 2022/004, International Monetary Fund.

Levine, Ross, and David Renelt, 1992, “A Sensitivity Analysis of Cross-Country Growth Regressions”, *American Economic Review*, 82(4), 942-963.

Prasad, Eswar, 2021, *The Future of Money: How the Digital Revolution is Transforming Currencies and Finance*, Harvard University Press.

Rogoff, Kenneth, 2017, *The Curse of Cash: How Large-Denomination Bills Aid Crime and Tax Evasion and Constrain Monetary Policy*, Princeton University Press

Sala-i-Martin, Xavier, 1997, “I Have Just Run Two Million Regressions”, *American Economic Review*, 87(2), 178-183.

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Appendix I. Alternative Data on Crypto Adoption

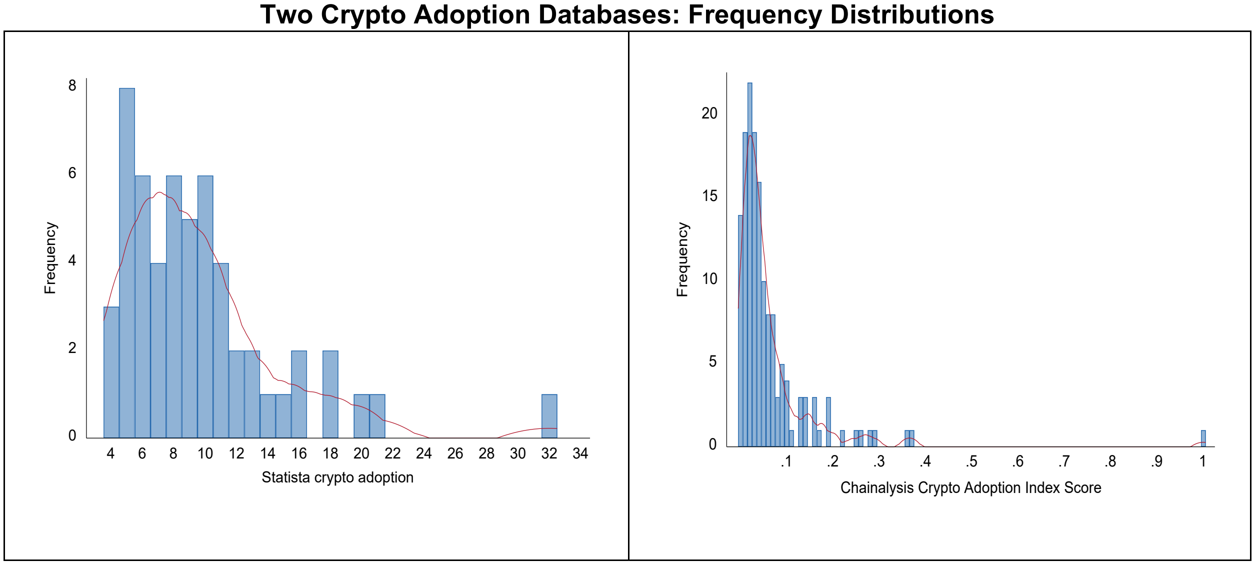
Chainalysis' 2021 Global Crypto Adoption Index has a wide coverage, with 154 countries. However, the index relies on web traffic data, and the usage of VPNs and other products that mask online activity can lead to errors in the estimation of crypto use and in assigning crypto use to specific countries.

Values of the Chainalysis crypto adoption index (RHS chart) have a highly skewed distribution, with most values concentrated close to zero, while a few implausible outliers produce a long right tail of the distribution (we exclude the largest outlier in the regressions using the index). Statista's measure (LHS) based on the survey responses is also skewed with some outliers, but overall has a more normally shaped distribution.

The two datasets also differ in their ranking of countries in terms of their adoption of cryptocurrency. Only four countries make it into the top ten crypto adopters in both datasets, which is also consistent with their relatively low correlation of 0.43.

Overall, based on available information, we consider that the Statista measure of crypto adoption has a more plausible distribution and avoids the likely mis-allocation of crypto use across countries due to the use of VPNs.

Two Crypto Adoption Databases: Frequency Distributions



With all these caveats on the use of Chainalysis crypto adoption index listed above, we have repeated our analysis with this alternative crypto adoption indicator. Using the different index allows to increase the sample size of the regression from 53 to 126. The coefficients of explanatory variables largely maintain their signs, and for control of corruption and capital controls the coefficients are very similar in magnitude to those reported in Table 3. The coefficients of both control of corruption and capital openness are significant and survive the redundancy test. This finding is robust in various regression specifications. This set of regressions also indicates a stronger and more significant negative association between crypto usage and the level of financial development (as proxied by the number of bank branches).

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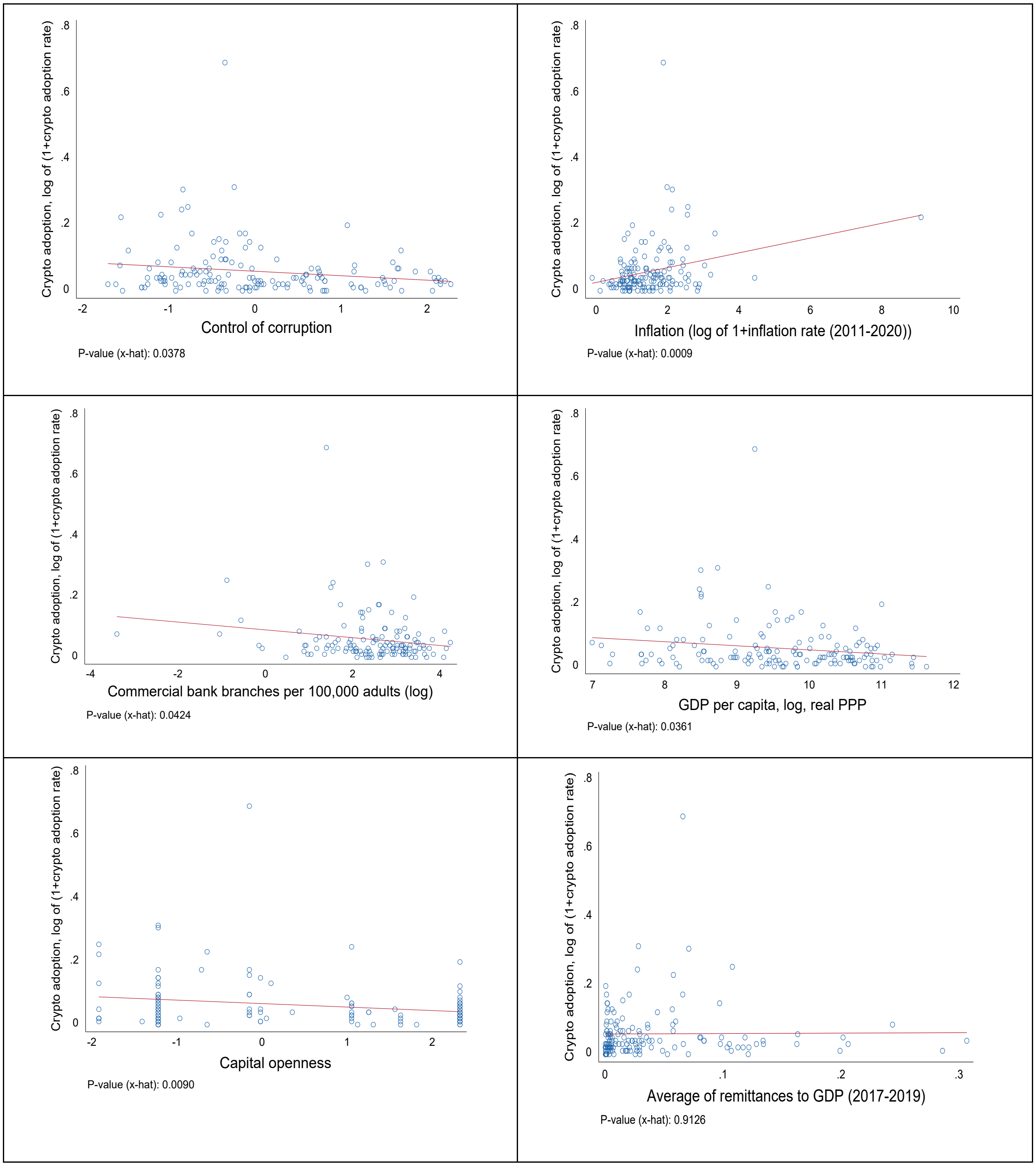
Chainalysis Crypto Adoption and Potential Explanatory Factors (continued)



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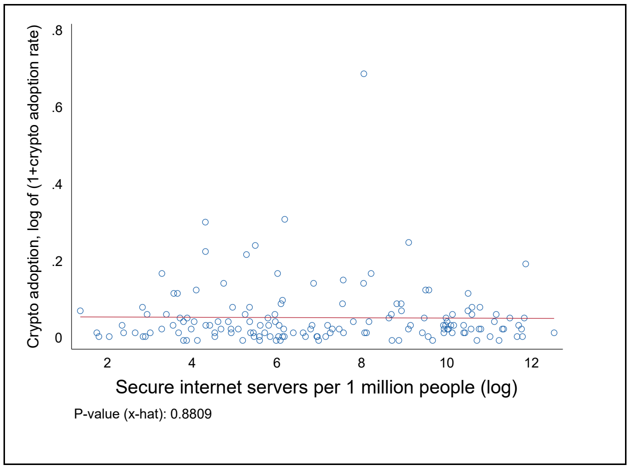
Chainalysis Crypto Adoption and Potential Explanatory Factors (concluded)



Sources: Chainalysis 2021 Global Crypto Adoption Index, Worldwide Governance Indicators, IMF World Economic Outlook, IMF Global Debt Database, IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER), IMF Financial Access Survey, WB Population Estimates, IMF Staff Calculations.

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Descriptive Statistics with Chainalysis Crypto Adoption

Variables	Mean	Median	Std. dev.	Min	Max
Crypto adoption (log of (1+crypto adoption rate))	0.062	0.039	0.083	0.000	0.693
Control of corruption (index)	0.126	-0.066	0.985	-1.572	2.270
Inflation (log of 1+inflation rate (2011-2020))	1.400	1.292	0.708	-0.124	4.429
Real GDP per capita (log, PPP 2017, international dollars)	9.623	9.694	1.031	6.987	11.445
Capital openness (index)	0.729	1.049	1.543	-1.924	2.322
Commercial bank branches (log, per 100,000 adults)	2.367	2.581	1.102	-3.413	4.231
Average of remittances to GDP (2017-2019)	0.043	0.019	0.060	0.000	0.306
Secure internet servers (log, per 1 million people)	7.326	7.140	2.826	1.349	12.532

Note: Descriptive statistics are for the 127 countries in the regression sample.

Pairwise Correlations Chainalysis Crypto Adoption

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Crypto adoption (log of (1+crypto adoption rate))	1.00							
(2) Control of corruption (index)	-0.17** (0.04)	1.00						
(3) Inflation (log of 1+inflation rate (2011-2020))	0.27*** (0.00)	-0.47*** (0.00)	1.00					
(4) Real GDP per capita (log, PPP 2017, international dollars)	-0.17** (0.04)	0.71*** (0.00)	-0.39*** (0.00)	1.00				
(5) Capital openness (index)	-0.22** (0.01)	0.55*** (0.00)	-0.34*** (0.00)	0.57*** (0.00)	1.00			
(6) Commercial bank branches (log, per 100,000 adults)	-0.18** (0.04)	0.29*** (0.00)	-0.36*** (0.00)	0.45*** (0.0)	0.25*** (0.00)	1.00		
(7) Average of remittances to GDP (2017-2019)	0.01*** (0.91)	-0.31*** (0.00)	0.10 (0.18)	-0.36*** (0.00)	-0.18** (0.02)	0.05 (0.55)	1.00	
(8) Secure internet servers (log, per 1 million people)	-0.01 (0.88)	0.74*** (0.00)	-0.34*** (0.00)	0.85*** (0.00)	0.53*** (0.00)	0.46*** (0.00)	-0.25*** (0.00)	1.00

Note: p-values are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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Empirical Results with Chainalysis Crypto Adoption as Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)
Control of corruption (index)	-0.019**	-0.023**	-0.026***	-0.026***
	(-2.118)	(-2.577)	(-2.775)	(-2.659)
Capital openness (index)	-0.010**	-0.011**	-0.013***	-0.012***
	(-2.274)	(-2.442)	(-2.807)	(-2.719)
Commercial bank branches	-0.011	-0.013	-0.014*	-0.015**
(log, per 100,000 adults)	(-1.366)	(-1.604)	(-1.778)	(-2.070)
Secure internet servers	0.014**	0.014**	0.011**	0.011**
(log, per 1 million people)	(2.339)	(2.371)	(2.350)	(2.596)
Average of remittances to GDP	-0.140	-0.135	-0.092	
(2017-2019)	(-1.655)	(-1.599)	(-1.102)	
Real GDP per capita,	-0.017	-0.017		
(log, PPP 2017, international dollars)	(-1.429)	(-1.464)		
Inflation	0.011			
(log of 1+inflation rate (2011-2020))	(1.038)			
Constant	0.148	0.172*	0.034	0.028
	(1.554)	(1.873)	(1.645)	(1.484)
Observations	126	126	126	127
R-squared	0.159	0.153	0.143	0.140

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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PUBLICATIONS

Crypto, Corruption, and Capital Controls: Cross-Country Correlations
Working Paper No. **WP/2022/060**