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Crypto-assets, corruption, and capital controls: Cross-country correlations

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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 corruption and 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.

1. Introduction

The emergence of crypto-assets (private digital assets that depend 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.[2] These developments create opportunities as well as risks. As noted by 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".[3]

The pseudonymity of crypto-assets (transactions require only digital identities) makes them a potential vehicle for illicit flows, including proceeds from corruption. 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 make it possible to move even larger amounts speedily and with greater ease, including across national borders (Graf von Luckner et al.).[4] As crypto-assets rapidly gain macroeconomic relevance (IMF 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, 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.[5]

Empirical investigation of the factors underlying the growing usage of crypto-assets is in its infancy, owing to data limitations.

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1 The views expressed in this paper are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

2 Prasad (2021) provides a comprehensive survey and analysis of how digitalization is transforming currencies and finance.

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

4 This is not to negate potential benefits of the technologies that crypto-assets are based on, particularly if used for central bank digital currencies, subject to important tradeoffs between costs and benefits (Prasad, 2021). Additional benefits of digitalization in government are discussed in International Monetary Fund (2018).

5 Auer and Tercero-Lucas (2021) do not find evidence that crypto investors are motivated by distrust in fiat currencies.

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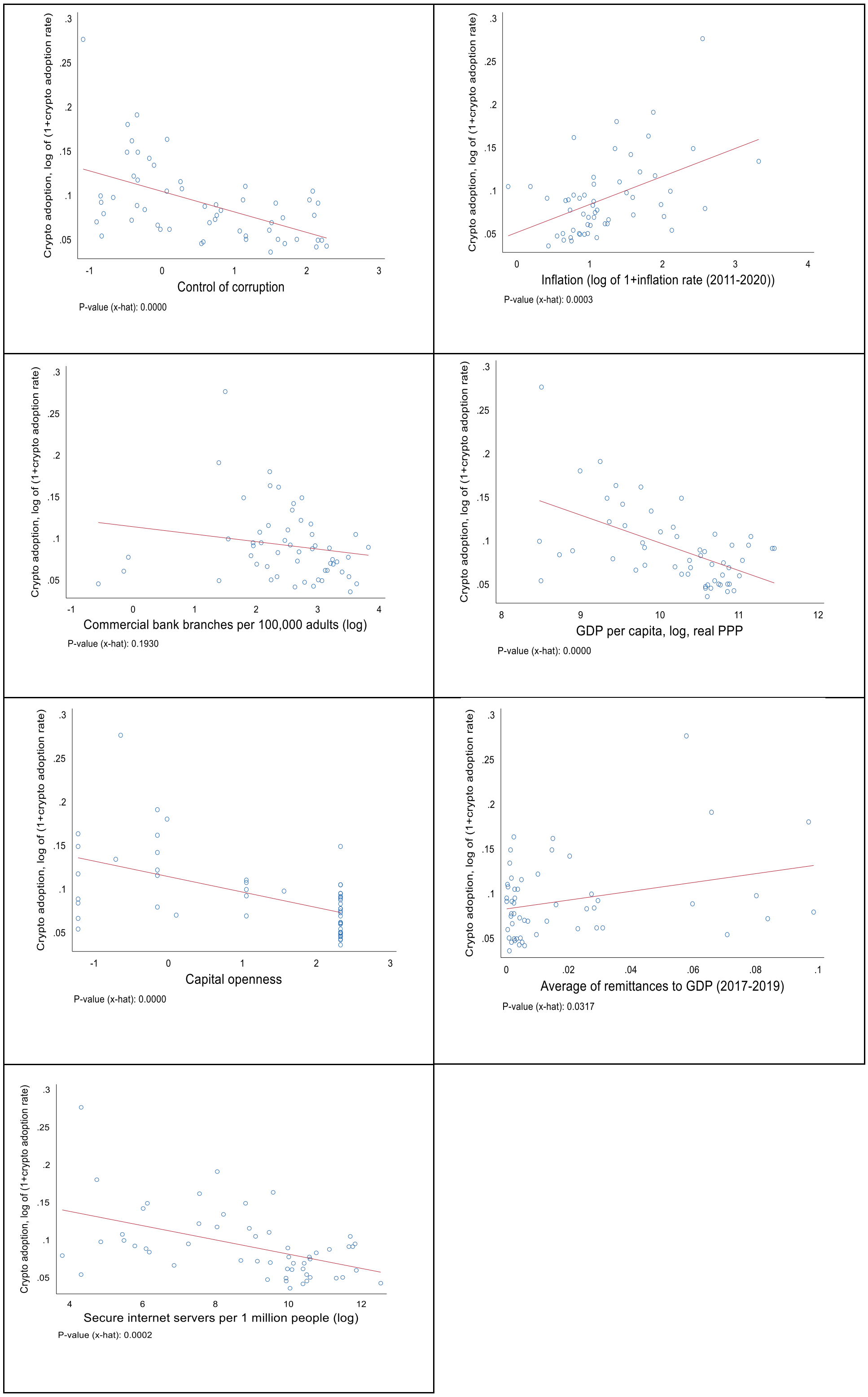

Fig. 1. Crypto-asset adoption and potential explanatory factors.

In this paper, we explore the correlation of crypto-asset usage with indicators of corruption, capital controls, a history of high inflation, and other factors, drawing on recent survey-based data. 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 imply 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.

Table 1
Descriptive statistics.

Variables	Mean	Median	Std. dev.	Min	Max
Crypto adoption log(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(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: The 53 countries in the regression sample 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.

Table 2
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Crypto adoption log(1+crypto adoption rate)	1.00							
(2) Control of corruption (index)	−0.53*** (0.00)	1.00						
(3) Inflation log((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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2. Data description and methodology

Our baseline data on crypto-currency usage are drawn from *Statista*, who collected them as part of their 2020 Global Consumer Survey.[6] The survey covered 55 countries, with 2000–12,000 respondents per country (we are unable to confirm whether respondents are representative of the population). The variable reflects the share of respondents who indicated they either owned or used cryptocurrencies in 2020. Given its skewed distribution, 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.

The list of explanatory variables (for 2020, unless otherwise indicated) includes the following:

- *Control of corruption index*, from the World Bank's Worldwide Governance Indicators.[7] The index combines the views of enterprise, citizen, and expert survey respondents in an aggregate index.
- *Average consumer price inflation rate for 2011–20*, from the IMF's *World Economic Outlook*. To reduce the weight of influential observations, a logarithmic transformation is applied: log(1+inflation rate).
- *Capital openness*, overall capital account openness index is derived using the methodology developed in Chinn and Ito (2008). Higher values of the index imply greater financial openness. The latest available value of this index is for 2019.
- *Logarithm of real GDP per capita in PPP terms*, as a general proxy for economic development.
- *Average Remittances for 2017–19* in percent of GDP. Data for 2020 are not included to avoid the effects of the COVID-19 pandemic shock.
- *Logarithm of commercial bank branches* per 100,000 adults, from IMF's Financial Access Survey, as a proxy for domestic financial development and inclusion. Residents of countries with a well-developed traditional financial sector may be less likely to use crypto-assets.

6 Other potential data sources for crypto-currency usage suffer from greater methodological drawbacks for empirical analysis (Appendix).

7 The results are essentially identical (not shown for brevity) using Transparency International's corruption perceptions index.

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	−0.014	−0.014	−0.013	−0.015**	−0.014*
	(−1.384)	(−1.406)	(−1.422)	(−1.644)	(−2.142)	(−1.984)
Capital openness (index)	−0.009	−0.009	−0.009	−0.009	−0.009*	−0.011*
	(−1.184)	(−1.425)	(−1.560)	(−1.580)	(−1.885)	(−2.008)
Commercial bank branches (log, per 100,000 adults)	−0.009	−0.009	−0.009	−0.009	−0.009	
	(−1.424)	(−1.411)	(−1.433)	(−1.496)	(−1.473)	
Real GDP per capita, (log, PPP 2017, international dollars)	−0.006	−0.006	−0.006	−0.004		
	(−0.362)	(−0.363)	(−0.348)	(−0.261)		
Secure internet servers (log, per 1 million people)	0.001	0.001	0.001			
	(0.233)	(0.236)	(0.267)			
Average of remittances to GDP (2017–2019)	−0.026	−0.026				
	(−0.073)	(−0.074)				
Inflation log(1+inflation rate) (2011–2020)	−0.000					
	(−0.019)					
Constant	0.189	0.189	0.183	0.177	0.136***	0.114***
	(1.107)	(1.087)	(1.096)	(1.051)	(6.451)	(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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.1
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.

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

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

Table A.3
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 (log, per 100,000 adults)	−0.011	−0.013	−0.014*	−0.015**
	(−1.366)	(−1.604)	(−1.778)	(−2.070)
Secure internet servers (log, per 1 million people)	0.014**	0.014**	0.011**	0.011**
	(2.339)	(2.371)	(2.350)	(2.596)
Average of remittances to GDP (2017–2019)	−0.140	−0.135	−0.092	
	(−1.655)	(−1.599)	(−1.102)	
Real GDP per capita, (log, PPP 2017, international dollars)	−0.017	−0.017		
	(−1.429)	(−1.464)		
Inflation (log of 1+inflation rate (2011–2020))	0.011			
	(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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

- *Logarithm of secure internet servers* per 1 million people, from World Bank's population estimates, as control for internet penetration and digitalization of the economy.

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 (Fig. 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, real GDP per capita and capital controls.

3. 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) was used to exclude potentially redundant variables. The Variance Inflation Factor (VIF) analysis confirms that multicollinearity is present, which implies the need to ascertain which variable(s) among the multicollinear ones carry the primary correlation with the dependent variable.[8]

The results indicate that the empirical association of crypto adoption with control of corruption and capital account openness is statistically significant (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 are the strongest performers that survive the elimination of the least significant variables.[9] At the last stage, it was not possible to distinguish between these two in terms of the level of significance, and neither was redundant. 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 toward stronger control of corruption and more capital openness (all else equal) is associated with a decline in crypto adoption by around 2 and 4 percentage points, respectively. These findings are robust to many variations of the explanatory variables. They are also not affected by removing potentially influential observations from regressions, like significant outliers in crypto usage and average inflation.

4. 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 the 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 on using the underlying technologies to improve financial inclusion or government efficiency.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[8] The VIF is a measure of collinearity among explanatory variables in a regression. A VIF value above 4 is considered to indicate the presence of significant multicollinearity. Variables in this regression have an average VIF of 3.74, with GDP and control of corruption having VIFs above 4.

[9] The F-statistics for the joint elimination of the other explanatory variables is 0.22, corresponding to a *p*-value of 0.88.

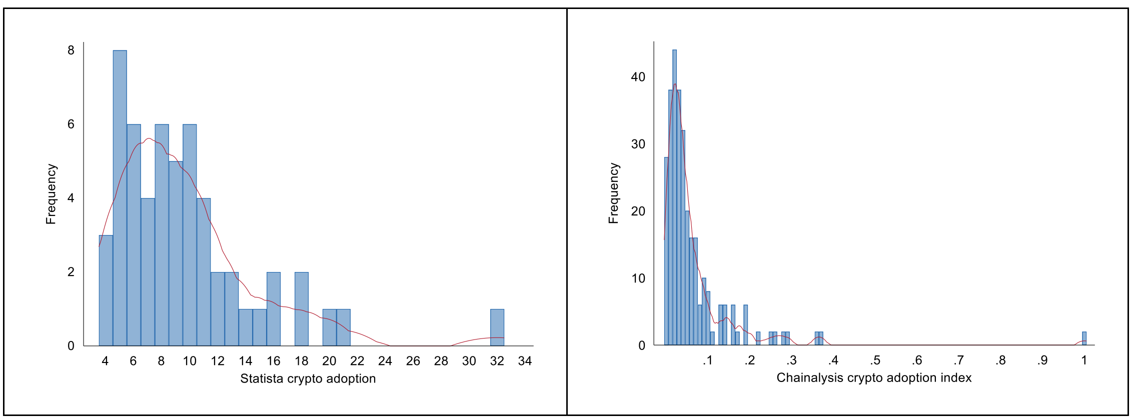
Appendix. Alternative data on crypto adoption

Chainalysis' 2021 Global Crypto Adoption Index has a wide coverage, with 154 countries.[10] 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. A second alternative dataset, from Finder, is based on surveys with a large 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; however, for the sake of completeness and transparency, we repeated our estimation using the Chainalysis data and report the results here. 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 misallocation of crypto use across countries due to the use of VPNs.

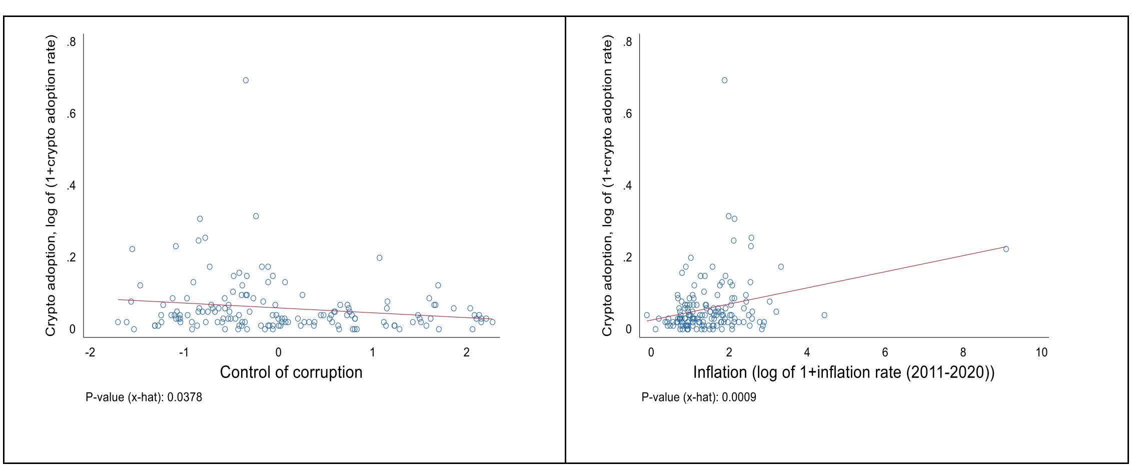
Two Crypto Adoption Databases: Frequency Distributions



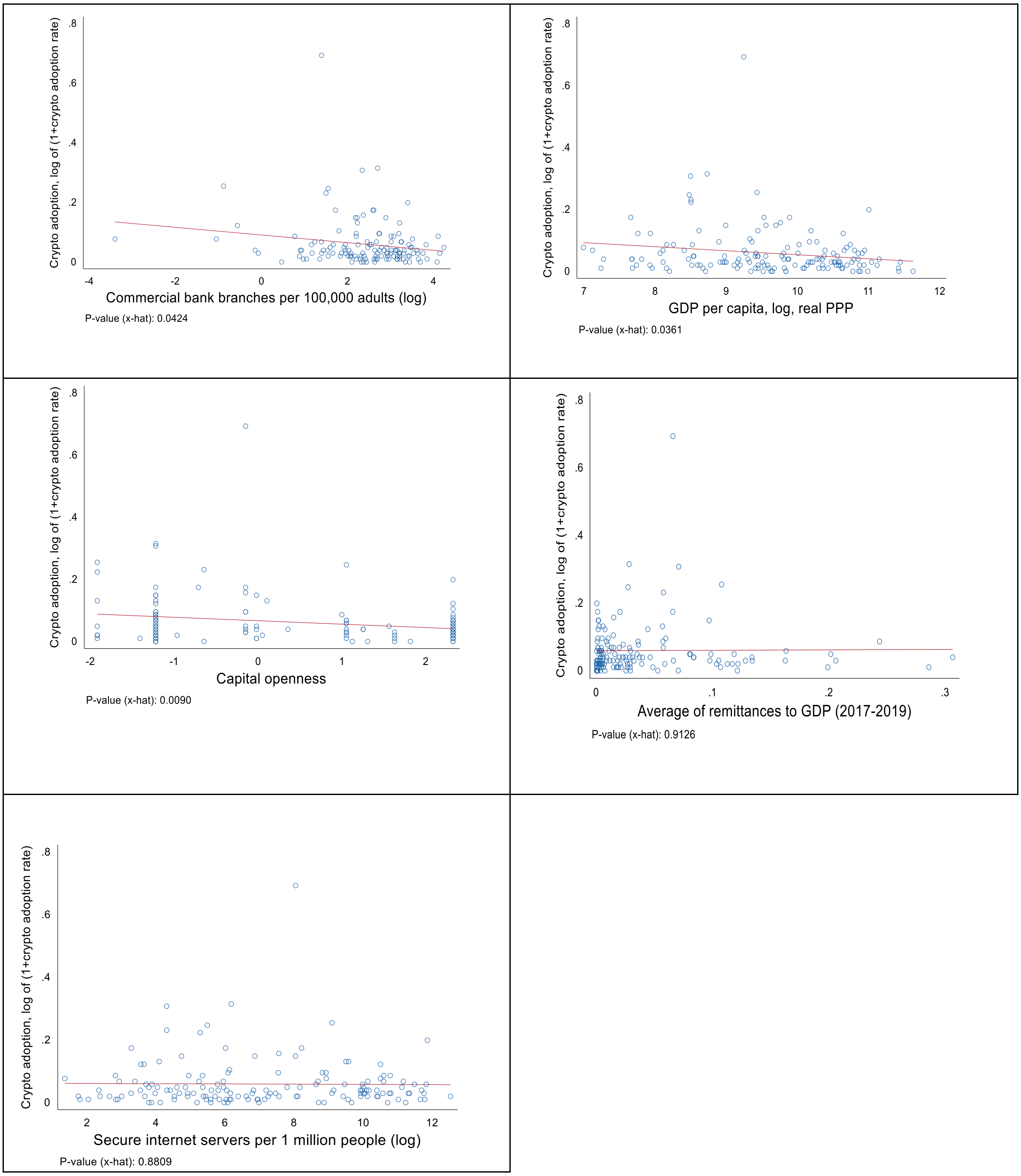
With all the caveats on the use of Chainalysis crypto adoption index listed above, we have repeated our analysis with this alternative crypto adoption indicator. Using the different index allows to increase the sample size of the regression from 53 to 126. The coefficients of the explanatory variables 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. As in Table 3, the coefficients of 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.

See Tables A.1–A.3.

Crypto adoption data from Chainalysis and potential explanatory factors



[10] The index covers the period July 2020–June 2021 and 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.


Crypto adoption, log of (1+crypto adoption rate)
Commercial bank branches per 100,000 adults (log)
P-value (x-hat): 0.0424
GDP per capita, log, real PPP
P-value (x-hat): 0.0361
Capital openness
P-value (x-hat): 0.0090
Average of remittances to GDP (2017-2019)
P-value (x-hat): 0.9126
Secure internet servers per 1 million people (log)
P-value (x-hat): 0.8809

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