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Corruption and crypto participation: Cross-country evidence

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Abstract

Inspired by the vast literature on stock market participation, this paper examines the relationship between corruption levels and crypto participation rates around the world. The issue is directly relevant to the ongoing debate on the factors that influence crypto adoption. We run cross-country regressions on data collected from various sources to examine crypto participation rates. Results provide preliminary evidence to support the claim that countries with higher levels of corruption tend to have higher crypto participation rates. The analysis and findings of this paper are relevant for assessing the socioeconomic implications of the inception and growth of the crypto movement.

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Corruption and Crypto Participation: Cross-country Evidence

1. Introduction

The motivating factors driving the growth of the crypto movement are often traced to the ideals of libertarianism and crypto-anarchism (Brunton, 2019; Chohan, 2017). In spite of these commendable ideals and the excitement surrounding potentially endless series of revolutionary developments based on blockchain and cryptocurrencies, regulators have remained largely unimpressed by the phenomenon of cryptocurrencies. Barring a few exceptions, governments and regulators have taken a predominantly sceptical, if not belligerent, view of the emergence and growth of crypto assets. This hostile stance stems from a range of factors including serious concerns related to money laundering, terrorism funding, challenges to monetary policy formulation and implementation, and potential threat of disruption to the existing model of financial intermediation. Perhaps the most vexing issue is the link between crypto industry and money laundering. What appears to be an exciting new technology promising revolutionary changes is simultaneously a new tool that aids criminal activities, including money laundering and corruption.

Available data appears to underscore the growing role of cryptocurrencies in facilitating money laundering and corruption. As estimated by Chainalysis (2023), cryptocurrencies worth nearly $ 23.8 billion were sent from illicit addresses in 2022, as compared to $ 14.2 billion in 2021 and $ 8.5 billion in 2020, representing a compounded annual growth rate of nearly 67%. To put this into proper context, it is useful to compare these numbers with the estimates of the total size of money laundering worldwide. According to United Nations Office on Drugs and Crime (UNODC, n.d.), the total amount of money laundered annually is nearly 2 to 5% of global GDP or nearly $ 800 billion to $ 2 trillion. The total market capitalisation of cryptocurrencies, at its peak in November 2021, was nearly $ 2.9 trillion and is hovering around $ 1.4 trillion in November 2023. In comparison, the estimated total money supply (M1) in the world was nearly $ 48.9 trillion in November 2022 (Desjardins, 2022). Back-of-the-envelope calculations from these estimates suggest that the role of cryptocurrencies in facilitating money laundering amounts to only a relatively small fraction (between 1% and 3%) of the total size of money laundering taking place worldwide, even though the numbers are growing.

In theory, it is not difficult to argue that the special characteristics of crypto assets make them perfectly suited for money laundering. There exists plenty of anecdotal evidence to suggest that criminal activities may be the driving force of adoption and growth of crypto assets around the world. If this hypothesis is correct, crypto adoption and prevalence of corruption should go together. But, are these beliefs and arguments supported by empirical data? This paper makes an attempt to address this question.

Not many studies have tried to assess empirically the use of crypto assets for criminal activities. To some extent, it may be the outcome of unavailability of data due to lack of regulation and centralised bodies in a movement that thrives on privacy, anonymity, and decentralisation. However, the public availability of blockchain with a complete record of pseudonymous transactions, allows it to be analysed to get insights into the nature of activities being carried out using crypto assets. Starting with seizures of bitcoin by law

enforcement authorities as a sample of users involved in illegal activities, Foley *et al*. (2019) employ a couple of empirical approaches to estimate that 26% of bitcoin users are involved in illegal activity. They also find that nearly 46% of bitcoin transactions are associated with illegal activities. The Crypto Crime Reports of Chainalysis (2022, 2023) analyse the trend of usage of cryptocurrencies for criminal activities.

These studies have touched upon only some aspects of the criminal activities associated with crypto industry. Many important questions regarding the link between crypto adoption and criminal activities still remain unanswered. In order to address some of these questions, this paper explores the link between prevalence of corruption and crypto participation rates around the world, and attempts to find preliminary empirical evidence based on available data.

This study contributes to the nascent literature in several ways. To the best of our knowledge, this is one of the first studies to examine the relationship between cross-country corruption levels and crypto participation rates. While there is a well-developed body of literature on stock market participation, there appears to be very little literature on crypto participation or adoption. As equities and crypto assets differ fundamentally in several ways, it will be interesting to compare the factors that determine participation in the stock markets and crypto markets, respectively. Moreover, this paper has implications for designing appropriate regulations for the crypto industry, especially in the context of countering money laundering and corruption.

The rest of the paper is organized as follows. The next section describes the use of cryptocurrencies in criminal activities and the development of the research hypothesis. Section 3 outlines the methodology and data employed for empirical analysis. Section 4 discusses the empirical results. Finally, Section 5 covers the concluding remarks and limitations.

2. Use of cryptocurrencies in criminal activities

Tracing the history of cryptocurrencies, it will not be wrong to conclude that their inception and development was chiefly inspired by the ideals of libertarianism and crypto-anarchism, with great emphasis on the features of privacy, anonymity, and decentralization (Brunton, 2019; Chohan, 2017). But these eminently justifiable features can also become perfectly handy tools for committing financial crimes.

It is useful to identify three categories of criminal activities associated with crypto assets (Larkin *et al*., 2022). The first category consists of crimes originating in and specific to the crypto industry. This includes crimes like cryptocurrency thefts or fraudulent initial coin offerings. The second category includes crimes which are facilitated by cryptocurrencies. Cryptocurrencies play a crucial role in enabling ‘black e-commerce’, i.e., the trade of illegal goods and services like drugs, weapons, and other restricted items, on the darknet marketplaces using cryptocurrencies (Foley *et al*., 2019). In this role, cryptocurrencies are effectively playing a helping hand in taking traditional illegal markets from streets to online mode. The third category includes crimes like money laundering, which has been linked to corruption.

Money laundering refers to the process of assimilating ill-gotten wealth into the mainstream financial system. The source of this ill-gotten wealth could be crimes involving crypto assets or crimes like corruption, including bribery and tax evasion. Cash has traditionally been the most convenient payment technology for criminal activities. But cryptocurrencies have emerged as close substitutes to cash in such transactions (Hendrickson and Luther, 2021). In fact, the entire spectrum of crypto assets may appear to be very suitable for money laundering, at least on a moderate scale. The 2022 Crypto Crime Report of Chainalysis (2022) points towards the increasing use of cryptocurrencies, decentralized finance (De-Fi) protocols, and non-fungible tokens (NFTs) for money laundering. They report that the usage of De-Fi protocols for money laundering witnessed a growth rate of 1964% during 2020-21.

The distinguishing features of crypto assets may be seen as potentially facilitating money-laundering. This can be demonstrated at each of the three steps into which the process of money laundering can be broken down: placement, layering, and re-integration (Albrecht *et al*., 2019; Hou, 2022). The ease with which cryptocurrencies can be employed to transfer funds across borders shows the potential advantage of using cryptocurrencies in the money laundering process (Fletcher et al., 2021). To a certain extent, this was demonstrated following the outbreak of the Russia - Ukraine war, when Binance Coin (BNB) was probably used for transferring funds across borders as an alternative tool to settle international transactions. This claim is consistent with the empirical findings of Arouri *et al.* (2023), who examined the abnormal returns of the top ten cryptocurrencies around the Russia-Ukraine war, and found positive abnormal returns only for Binance Coin. This example demonstrates the potential use of cryptocurrencies as a tool to circumvent international economic and financial sanctions.

In this paper, we probe further the anecdotal evidence on use of crypto assets for money laundering. If money laundering is an important use case of crypto assets, we expect to find a significant relationship between levels of corruption and crypto participation. Testing this empirically with available cross-country data is the main objective of this paper.

As we have defined crypto market participation analogously to stock market participation, the use of any of the thousands of crypto assets qualifies as participation in the crypto market. This method of assessing crypto participation ignores the differences in crypto assets. Different crypto assets are designed to offer different levels of privacy, anonymity, decentralization, and other features. Some of these features make some crypto assets (especially the privacy tokens, such as Monero or Zcash) relatively more suitable for money laundering. Ignoring these finer differences among crypto assets with respect to their suitability for money laundering, amounts to a limitation of the study. Extensive usage of some crypto assets for money laundering and higher adoption of such crypto assets by countries having lower aggregate level of crypto adoption, may lead to outcomes that are inconsistent with the results of this study.

From a larger perspective, the relationship between corruption and participation in the markets of various asset classes is very important. Previous studies have examined it in the case of equities. In a recent paper, Bu *et al*. (2022) show that households with higher exposure to political corruption tend to participate less in the stock market. Although their study is based on household-level data of the impact of anti-corruption campaigns in China, it is noteworthy that they find a negative relationship between exposure to corruption and stock

market participation. It will be interesting to see if the relationship between corruption and asset market participation is different in case of stock markets and crypto markets.

3. Methodology and Data

Our analysis is based on cross-country regressions with a set of control variables. We use suitable measures of crypto participation rates as dependent variable and an index of cross-country corruption levels as independent variable of primary interest. As familiarity with the internet, educational level, and income level are considered to be important factors in an individual investor's decision to participate in the crypto market, we have used country-level internet penetration, average years of total schooling, and log GDP per capita (PPP) as control variables. This approach is guided by similar cross-country regressions employed by Guiso *et al*. (2008) and Ke (2018) to study stock market participation rates. In addition, we also control for country-level financial development as it reflects the depth, access, and efficiency of the financial institutions and markets available to the investor and plays an important role in the dynamics of income inequality in the country (Mathonnat and Williams, 2020).

Given the nature of secrecy surrounding them, it is difficult to obtain accurate data on crypto participation and corruption, more so, at the cross-country level. As different datasets were collected at different points of time across different countries with different objectives, we do not have a dataset where various variables correspond exactly to one another. This limitation notwithstanding, we managed to compile relevant data from various sources.

Data on Crypto Participation Rate has been taken from Statista Global Consumer Survey for the years 2019-2021. This survey is based on the response to the following question by 2000 to 12000 respondents per country in 56 countries: "Which of these financial products/ investments do you currently use/ own? (multi-tick)". Respondents who chose the option "Cryptocurrency (e.g., Bitcoin)" are counted as users/ owners of cryptocurrencies. Proportion of such respondents is taken as the Crypto Participation Rate (CYP) for the country. It is defined analogously to the stock market participation rate.

As an alternative measure of participation in the crypto markets, we use Crypto Adoption Index (CAI) developed by Chainalysis (2021) on the basis of three metrics: on-chain cryptocurrency value received by a country weighted by per capita GDP (PPP), on-chain value received by a country in retail transactions (defined as transactions for under $ 10,000 worth of cryptocurrency) weighted by per capita GDP (PPP), and peer-to-peer (P2P) trade volume weighted by per capita GDP (PPP) and number of internet users. Using suitably-weighted trade volume data, this index intends to assess the cryptocurrency adoption level in a country. It is worth noting that the Crypto Adoption Index, as defined by Chainalysis, is different from the Crypto Participation Rate described in the previous paragraph.

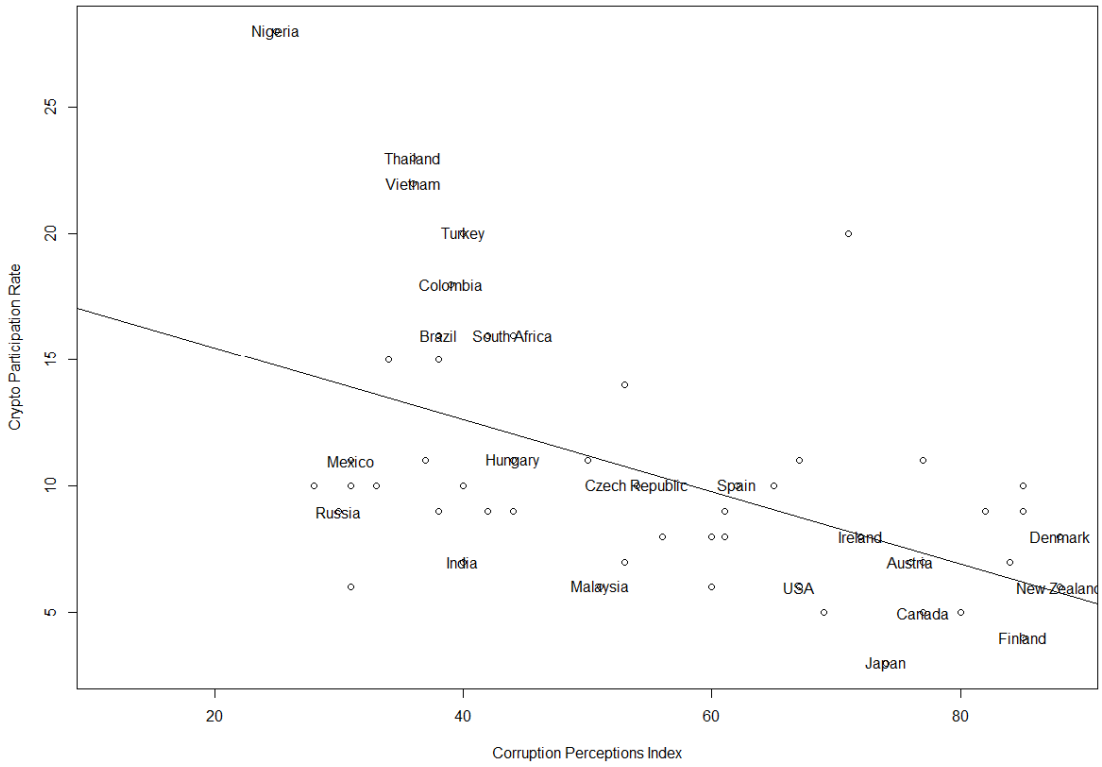
As a measure of corruption levels worldwide, we have used Corruption Perceptions Index (CPI) of Transparency International (2021). This index ranks countries on the basis of

perceived levels of public sector corruption. This index uses a scale that varies from 0 (highly corrupt) to 100 (very clean). Hence, a lower index value implies a higher corruption level.

We use several country-level controls assembled from different sources. The data on internet users as a proportion of the population of the country, has been compiled from the data on internet users and population available on Internetworldstats.com. Data on per capita GDP (PPP) in the year 2020 has been taken from the World Bank, World Development Indicators database. The data on average years of total schooling has been compiled from Barro-Lee Educational Attainment Dataset of Barro and Lee (2021). Finally, the Financial Development Index database of the International Monetary Fund (2021) has been used to control for country-level financial development.

Figure 1 shows the relationship between Crypto Participation Rate (CYP) and Corruption Perceptions Index (CPI) of 56 countries for which data are available. To avoid cluttering of the graph, it shows names of only a few countries. The graph shows clearly that a strong negative correlation exists between CYP and CPI. As higher value of CPI implies less corruption, the graph shows that crypto participation tends to be higher in countries with higher perceived level of corruption.

Figure 1: Corruption Perceptions Index and Crypto Participation Rate across Countries



4. Empirical results

The results are summarized in Tables I-III. As dependent variable, we have used three different measures of crypto participation rate: crypto participation rate for the year 2019 (CYP), average of crypto participation rates over 2019-22 (CAV), and Chainalysis Crypto Adoption Index 2021 (CAI).

Table I summarizes the results of the regression with CYP as the dependent variable. The result that the coefficient of CPI remains negative and significant in all the four specifications shows that there is a strong positive relationship between crypto participation and corruption level, even after adjusting for all the control variables. The negative coefficient of CPI is appropriate because of the inverse relationship between CPI and level of corruption.

Table I: Corruption Perceptions Index and Crypto Participation Rate around the World

Crypto Participation Rate (CYP)					
	(1)	(2)	(3)	(4)	(5)
Corruption Perception Index (CPI)	-0.14269*** (0.03035)	-0.17723*** (0.04476)	-0.12392** (0.04532)	-0.16543** (0.05137)	-0.16261** (0.05546)
Internet penetration		0.06105 (0.05820)	0.07070 (0.05891)	0.01476 (0.06676)	0.01903 (0.07365)
Average years of total schooling			-0.54064 (0.43975)	-1.12984* (0.55395)	-1.12944* (0.55958)
Log GDP per capita (PPP)				3.57968 (2.09670)	3.54748 (2.12972)
Financial Development					-0.56626 (3.92873)
Observations	56	56	55	54	54
R-squared	0.2904	0.3049	0.2846	0.3256	0.3258

Note: Standard errors are reported in parentheses. *** indicates the coefficient is different from 0 at the 0.1% level of significance, ** at the 1% level, and * at the 5% level.

As a second measure of crypto participation rate, we use the average participation rate over three years 2019-22. The results of regression with this measure are shown in Table II. Using the same set of control variables, we find similar results: CPI coefficient remains negative and significant across all the four specifications.

Table II: Corruption Perceptions Index and Average Crypto Participation Rate around the World

Average Crypto Participation Rate (CAV)					
	(1)	(2)	(3)	(4)	(5)
Corruption Perception Index (CPI)	-0.14199*** (0.03186)	-0.16212** (0.04733)	-0.09052* (0.04330)	-0.10350* (0.05037)	-0.11000* (0.05433)
Internet penetration		0.03559 (0.06153)	0.04323 (0.05628)	0.02917 (0.06546)	0.01933 (0.07214)
Average years of total schooling			-0.65972 (0.42010)	-0.81643 (0.54314)	-0.81735 (0.54812)

Log GDP per capita (PPP)				1.01618 (2.05577)	1.09039 (2.08610)
Financial Development					1.30511 (3.84827)
Observations	56	56	55	54	54
R-squared	0.2689	0.2735	0.2772	0.2781	0.2799

Note: Standard errors are reported in parentheses. *** indicates the coefficient is different from 0 at the 0.1% level of significance, ** at the 1% level, and * at the 5% level.

Finally, we use Crypto Adoption Index (CAI) prepared by Chainalysis as a proxy for crypto participation rate. It may be recalled that this measure is different from what we mean by crypto participation rate, i.e., the proportion of population participating in the crypto market. However, it may be used as a proxy for crypto participation rate. Results of the regression with CAI as the dependent variable are presented in Table III. Here we do not use per capita income as a control variable because the construction of CAI has already taken into account the cross-country differences in per capita income. CPI coefficient is of the right sign but it is not significant in the first specification which does not include control variables. But it becomes significant after adding the control variables in the remaining specifications. R-squared values for these regressions are substantially lower than those presented in Table I and III.

Table III: Corruption Perceptions Index and Crypto Adoption Index around the World

Crypto Adoption Index (CAI)				
	(1)	(2)	(3)	(4)
Corruption Perception Index (CPI)	-0.00084 (0.00045)	-0.00176** (0.00060)	-0.00163* (0.00071)	-0.00246** (0.00078)
Internet penetration		0.00099* (0.00043)	0.00135* (0.00056)	0.00088 (0.00060)
Average years of total schooling			-0.00690 (0.00555)	-0.00805 (0.00563)
Financial Development				0.14735* (0.06857)
Observations	146	146	128	124
R-squared	0.0230	0.0583	0.072	0.1088

Note: Standard errors are reported in parentheses. *** indicates the coefficient is different from 0 at the 0.1% level of significance, ** at the 1% level, and * at the 5% level.

5. Concluding remarks

As the empirical results clearly show, there is a strong relationship between corruption level of a country and its level of participation in the crypto market. Countries with higher levels of

corruption (i.e., lower corruption perceptions index) tend to have higher crypto participation rates.

Prima facie, this result appears to stand in stark contrast to the lofty ideals of libertarianism and crypto-anarchy that inspired the birth and growth of the crypto movement. But it is not difficult to reconcile with the fact that the key distinguishing features of crypto assets—anonymity without regulation—make them particularly suitable for criminal activities like money laundering and corruption. This underscores the importance of having appropriate regulation for crypto markets. Anonymity with proper regulation can make crypto assets less acceptable for criminal activities and more useful for realizing the genuine benefits of the new technology.

But these results only provide suggestive evidence regarding the link between corruption and crypto participation. This is essentially a cross-country study based on aggregate country-level data collected at different points of time with different objectives and methodologies. As discussed earlier, these results are also subject to the limitation imposed by ignoring the differences among crypto assets with respect to their suitability for money laundering. Moreover, the element of anonymity associated with crypto transactions and criminal activities severely restricts the availability of relevant data. In view of these limitations, this paper is only able to provide preliminary evidence regarding macro-level cross-country patterns.

It is also interesting to observe that the relationship between corruption and crypto market participation is not in line with the findings of Bu *et al*. (2022) in the case of relationship between corruption and stock market participation. While they find a negative relationship between exposure to corruption and stock market participation using household-level data in China, our study finds positive relationship between perceived levels of corruption and crypto market participation using cross-country data. They conclude that the effect of corruption is predominantly driven by households' trust and perception of institutional quality. Examining the relationships between corruption, trust, and participation in the markets of various asset classes is an important task for future research.

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