Financial crime risk and cryptocurrency : International evidence

Abstract

We examine the relationship between money laundering and terrorist financing (ML/TF) risk and cryptocurrency adoption and its impact on the cryptocurrency-stock correlations. Employing cross-country panel data, we find a positive and significant relationship between ML/TF risk and cryptocurrency adoption, suggesting that financial crime risk stimulates cryptocurrency adoption. We also observed a significant and positive relationship between cryptocurrency adoption and risk associated with the quality of anti-money laundering/counterterrorist financing (AML/CFT) frameworks, thus highlighting the importance of effective regulatory frameworks to combat cryptocurrency misuse. Additionally, we find a significant negative effect of ML/TF risk on cryptocurrency-stock correlations, indicating that cryptocurrencies can act as diversifiers in economies with high financial crime. However, regulatory and reputational risks may reduce the appeal of cryptocurrency as a stable investment asset.

Keywords: Cryptocurrency adoption, Financial crimes, Money laundering, Terrorist financing, Diversifier and Stock-cryptocurrency correlation

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1 Introduction

Over the past decade, the number of cryptocurrencies in the market has grown by more than 10,000, with a market capitalization of approximately 2.21 trillion dollars by the beginning of 2022 (Londoño & Alonso Díaz, 2024). The rapid growth of cryptocurrency and its anonymity to users have created considerable regulatory challenges, raising concerns about financial crimes (Foley et al., 2019). As most jurisdictions continue to work towards balancing financial inclusion and security concerns, it becomes more important to understand the influence of financial crime risk on cryptocurrency (IMF, 2023).

Literature exploring the darker aspects of the cryptocurrency market has revealed a strong association between illegal activity and cryptocurrencies. For instance, the seminal work by Foley et al. (2019) estimate that nearly half of cryptocurrency transactions and about onequarter of cryptocurrency users are involved in illegal activities. Similarly, Scharnowski (2024) find a positive association between dark web traffic and cryptocurrency trading activities, particularly privacy coins. Marmora (2021) provide evidence that cryptocurrency is increasingly being used as a substitute currency in the shadow economy, despite its limited acceptance in mainstream financial transactions. Almaqableh et al. (2023) presented empirical evidence of the impact of drug busts on cryptocurrency activities, indicating a direct link between cryptocurrency and drug trafficking activities. Corruption is another illicit activity that has been found to have a significant influence on cryptocurrency usage across countries (Alnasaa et al., 2022; Gonzálvez-Gallego & Pérez-Cárceles, 2021). Prior literature also terrorist activities influence the cryptocurrency market, suggesting that indicates that cryptocurrency has been used to fund terrorist organizations (Almaqableh et al., 2022). Although evidence suggests that cryptocurrencies are used for illicit activities, research on the impact of financial crimes, such as money laundering and terrorist financing, on cryptocurrency usage remains limited. We fill this gap in the literature by investigating the role of financial crime risk in cryptocurrency adoption across countries. Research also suggests that regulatory oversight may influence the volume and penetration of cryptocurrency assets(Coelho et al., 2021). However, empirical studies analyzing the impact of regulatory oversight, particularly concerning financial crime, on cryptocurrency usage remain scarce. Our paper intends to address this gap in the literature.

The evidence generated in these studies collectively suggests that the possibility of conducting illicit activity attracted the potential users of cryptocurrencies as a medium of exchange. This is conceivable since the seller of the illicit goods (e.g. illegal drugs) may prefer cryptocurrency to obscure the transaction(Baur et al., 2018).Perhaps more concerning is that cryptocurrency is been widely used as an asset contrary to its definition of alternative currency (Baur et al., 2018). Given the weak positive or negative correlation with the equities (Bouri et al., 2017; Dwita Mariana et al., 2021; Dyhrberg, 2016), cryptocurrencies have been classified as a new safe haven asset entering into the conventional safe-haven list of gold (Baur & Lucey, 2010), commodities (Badshah et al., 2019) and foreign currencies (Ranaldo & Söderlind, 2010).

However, the association between cryptocurrency and illicit activities raises concern about the long-term viability of cryptocurrencies as an investment tool. As highlighted by (Baur et al., 2018), the balance between potential users and investors ultimately determines the success of the cryptocurrency. Given that increasing the use of cryptocurrencies for illicit activities may lead to greater regulatory scrutiny and reputational risks, this could undermine the appeal of cryptocurrencies as a stable and legitimate investment asset. Hence, we also examine the

impact of financial crime risk due to money laundering and terrorist financing in a country's stock-cryptocurrency correlation.

Using cross-country data on cryptocurrency adoption and financial crime risk, we contribute to the literature on fintech and financial crime in the following ways. First, we augment the growing body of literature that explains the association between cryptocurrency and illicit activities (Alnasaa et al., 2022; Foley et al., 2019; Gonzálvez-Gallego & Pérez-Cárceles, 2021; Hendrickson & Luther, 2022; Marmora, 2021; Scharnowski, 2024) by investigating the impact of money laundering and terrorist financing (ML/TF) risk on cryptocurrency adoption. We report a positive relation between the examining factors, which contribute specifically to the crypto research on the usage of cryptocurrency, in particular concerning financial crimes. Second, building on the argument by Coelho et al. (2021) regarding the necessity of effective regulation and supervision to address ML/TF threats from crypto assets, we examined how the subcomponents of ML/TF risk affect cryptocurrency adoption. We observed a significant and positive relationship between cryptocurrency adoption and risk associated with the quality of anti-money laundering/counter-terrorist financing (AML/CFT) frameworks, thus highlighting the importance of effective regulatory frameworks to combat cryptocurrency misuse. Third, we add to the growing body of literature that explains the stock-cryptocurrency relationship (Bao et al., 2022; Bouri et al., 2017; Dwita Mariana et al., 2021; Dyhrberg, 2016; Oosterlinck et al., 2023) by identifying an important factor that causes a negative correlation between the cryptocurrency-stock market, namely, ML/TF risk. Finally, our study sheds light on the debate on whether cryptocurrencies are best classified as a medium of exchange or an investment (Baur et al., 2018; de la Horra et al., 2019; Smales, 2019). Our study provides empirical evidence for the argument of (Baur et al., 2018) by identifying economies where the number of potential users increases due to the possibility of utilizing for financial crimes determine the success of the cryptocurrency as a store of value.

The remainder of this paper is organized as follows. Section 2 describes the data and empirical methods used in this study. Section 3 reports the findings of the study. Finally, Section 4 concludes the paper.

2. Data

This study examines the relationship between ML/TF risk and cryptocurrency adoption, as well as its impact on the cryptocurrency-stock correlations. Hence we construct our sample in two phases. Our first phase sample consists of annual data for 114 countries from 2020 to 2023. We use the cryptocurrency adoption index constructed by Chainalysis¹ based on the web traffic patterns of cryptocurrency services and protocols. ML/TF risk data were obtained from the Basel Institute of Governance² where countries are scored based on the effectiveness and structures put in place to counter ML/TF threats. For our additional analysis, we obtained ML/TF risk subcomponents from the same source as the Basel Institute of Governance. Following previous literature (Alnasaa et al., 2022; Bhimani et al., 2022; Gonzálvez-Gallego & Pérez-Cárceles, 2021), we used a set of controls for country-specific factors that influence cryptocurrency adoption, including political stability and absence of violence/terrorism, GDP growth rate, inflation rate, human development index, compliance with judiciary, regulatory quality, absence of corruption, network readiness, crime index, and FATF recommendation-15

¹ https://www.chainalysis.com/blog/2023-global-crypto-adoption-index/#methodology

² https://index.baselgovernance.org/

obtained from the World Bank, International Monetary Fund (IMF), United Nations Development Programme (UNDP), Financial Action Task Force (FATF), and other statistical agencies.

For the second phase, we use data on cryptocurrency price index value, including Bitcoin and Ethereum, and country-level MSCI index across 73 countries. Based on the availability of the cryptocurrency data, our sample period constitutes two distinct periods. Bitcoin data covers the period from 1st January 2014 to 29th December 2023. Ethereum data spans from 1st January 2018 to 29th December 2023. The data on Bitcoin and Ethereum variables are obtained from the DataStream, while country-level stock market indices were acquired from MSCI³. Explanatory variable of ML/TF risk were collected from the Basel Institute of Governance⁴, which measures the risk of money laundering and terrorist financing of countries based on effectiveness and structures put in place. Following the existing literature of (Bao et al., 2022), we include a set of control variables, including economic variables (Exchange rate, Central Policy Rate, GDP, Inflation Rate, and Global economic policy rate(GEPU)) and financial market variable of the MSCI world volatility tilt index(MSCI WVTI).

3. Methodology

3.1 Financial crime risk and Cryptocurrency adoption

To assess how financial crime risk due to ML/TF risk influences the cryptocurrency adoption, we run the following regression model to test our hypotheses:

$$CA_{it} = \beta 0 + \beta 1 ML/TF_{it} + \varphi Controls_{it} + \varepsilon_{it}$$
(1)

where *i* and *t* denote the country and time, respectively, and ε is the error term. CA is the cryptocurrency adoption index, and ML/TF is the country level of money laundering and terrorist financing risk. Online Appendix A1 provides a detailed summary of the data, including the variable definitions and sources. Robust standard errors clustered at the country level. For the robustness test, we first use region-specific fixed effects regression to capture the unobservable heterogeneity specific to the regions. We also examine the impact of the one-year lagged variable of ML/TF risk and control variables on cryptocurrency adoption to rule out homogeneity. For our additional analysis, we consider the potential effect of ML/TF risk subcomponents on cryptocurrency adoption.

3.2 Measuring the correlation between the cryptocurrency and stock indices

The initial step in our empirical analysis is to estimate the co-movement between the cryptocurrency and country-level stock market indices by utilizing a time-varying measure of the DCC-GARCH model introduced by (Engle, 2002). The specification is a generalization of the (Bollerslev, 1990) constant conditional correlation (CCC) estimator., allowing the correlation matrix containing the conditional correlations to be time-varying (Engle, 2002). We first compute the daily return r_t of the assets (Bitcoin, Ethereum and MSCI indices) as the first difference of the natural logarithm of the price series for each asset:

$$\mathbf{r}_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

³ MSCI : https://www.msci.com/end-of-day-data-country

where P_t represents the price of the assets (Bitcoin, Ethereum, and MSCI indices) at time t. Meanwhile, the variance of the equation is as follows:

$$h_t = c + \alpha \epsilon^2_{t-1} + \beta h_{t-1} \tag{2}$$

where h_t is the conditional variance at time t, c is the constant term, α is the ARCH parameter that captures the short-term impact of shock on volatility and β is the GARCH parameter that captures the persistence of past volatility. The residuals from this step (ϵ_t) are standardized to obtain (z_t), which are used in the following correlation modelling step.

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1}$$
(3)

where Q_t is the conditional correlation matrix at time t, \bar{Q} is the unconditional correlation matrix of z_t , α is the impact of recent shocks on the correlation and β is the persistence of past correlations. From Q_t , the conditional correlations between assets i and j are extracted.

$$pij, t = \frac{qijt}{\sqrt{qii, t * qjjt}}$$

3.1 Financial crime risk and Cryptocurrency – Stock Correlation

To assess how financial crime risk due to ML/TF risk influences the cryptocurrency-stock comovement, we run the following regression model to test our hypotheses:

$$DCC_{it} = \beta 0 + \beta 1 ML/TF_{it} + \varphi Controls_{it} + \varepsilon_{it}$$
(1)

where *i* and *t* denote the country and time, respectively, and ε is the error term. *DCC* is the cryptocurrency – stock correlation, and ML/TF is the country level of money laundering and terrorist financing risk. Online Appendix A1 provides a detailed summary of the data, including the variable definitions and sources. Robust standard errors clustered at the country level. For the robustness test, we first use region-specific fixed effects regression to capture the unobservable heterogeneity specific to the regions. We also examine the impact of the one-year lagged variable of ML/TF risk and control variables on cryptocurrency adoption to rule out homogeneity. For our additional analysis, we consider the potential effect of ML/TF risk subcomponents on cryptocurrency adoption.

3. Results

3.1 Descriptive Statistics

Table 2A in the Appendix presents the descriptive statistics. The mean value of cryptocurrency adoption is 0.11, with a standard deviation of 0.158, indicating that approximately 11% of the sample countries adopt cryptocurrency. This finding suggests that most countries in the sample have relatively low levels of cryptocurrency adoption. The average value of ML/TF risk is 5.30 on a scale of 0-10, with a standard deviation of 1.121, indicating that the countries in the collected sample have moderate ML/TF risk. Additionally, the analysis of the subcomponents related to ML/TF risk indicates that the average perceived risk associated with the quality of AML/CFT is 5.604, with a standard deviation of 1.192, while the average of other subcomponents, including bribery and corruption risk (4.896), financial transparency and standard risk (4.876), public transparency and accountability (3.995) and legal and political risk (4.14) is moderate to high. Most of the country-specific control variable statistics are close

to those reported in the prior studies (Alnasaa et al., 2022; Bhimani et al., 2022; Gonzálvez-Gallego & Pérez-Cárceles, 2021).

Table 2B in the Appendix presents the descriptive statistics for the second phase of our analysis. The mean value of the Bitcoin-stock returns correlation is 0.09, with a standard deviation of 0.39, indicating a slight positive correlation on average, but with considerable variation across the sample. In contrast, the mean Ethereum-stock returns correlation is 0.35, with a standard deviation of 0.53, suggesting a moderate positive correlation, though with greater variability compared to Bitcoin. This highlights that while both cryptocurrencies positively correlate with stock returns, Ethereum exhibits more pronounced and diverse relationships across countries. The summary statistics of the other control variables are close to the prior studies (Bao et al., 2022).

3.2 Financial crime risk and cryptocurrency adoption

Table 2 presents the impact of financial crimes on the country-level cryptocurrency adoption. All the specifications in Table 2 highlight that the coefficient of our primary variable of interest is positive and statistically significant. Column 1 presents the results of estimating Equation (1) using an OLS regression. We find that a higher ML/TF risk increases cryptocurrency adoption, implying that an increase of one standard deviation in ML/TF risk increases cryptocurrency adoption by 24.12% [0.034*(1.121/0.158)]. These results clearly highlight that countries with greater financial crime risk have a high level of cryptocurrency adoption, implying that cryptocurrencies may be used to conceal and facilitate the proceeds of illicit activities. Column 2 employs OLS regression with clustered robust standard errors to correct for omitted variable bias (Nenova, 2003). Our positive and significant results persisted, reinforcing the initial findings. Additionally, we observed that the sign and significance of the control variables on cryptocurrency adoption are consistent with the findings of previous studies (Alnasaa et al., 2022; Bhimani et al., 2022; Gonzálvez-Gallego & Pérez-Cárceles, 2021).

Consistent with the notion that illegal practices promoted by cryptocurrency, including tax evasion or money laundering, incentives people to use those assets (Gonzálvez-Gallego & Pérez-Cárceles, 2021), our findings provide evidence that countries with higher financial crime risk due to money laundering and terrorism financing have higher cryptocurrency adoption. These results substantiate the findings of (Alnasaa et al., 2022; Foley et al., 2019; Marmora, 2021; Scharnowski, 2024) regarding cryptocurrency use for illicit activity. Compared to prior literature on the association between cryptocurrency and illicit activities, we provide new evidence on how financial crime risk shapes cryptocurrency adoption. Our results extend the existing literature by demonstrating that the risk of money laundering and terrorist financing facilitates cryptocurrency adoption. This suggests that individuals and organizations may leverage cryptocurrencies to navigate regulatory challenges and conceal illicit activities.

To ensure the robustness of our results, we first follow Chong and Lopez-De-Silanes (2015) to run regional fixed effects regression to account for the regional difference in money laundering and its regulation. The coefficient estimates reported in Column 3 of Table 2 remain consistent with the baseline models along with a significant improvement in the adjusted R-squared value. Second, we employed one-year lagged values of the independent and control variables in the model to rule out endogeneity concerns. The results presented in Column 4 indicate that the

initial result of positive significance persists over time, even extending to one-year lagged values. This is consistent with the notion that technological adoption may depend on the current and past behaviors of the relevant factors (Besley & Case, 1993).

Crypto adoption Score	(1)	(2)	(3)	(4)
ML/TF risk	0.034***	0.034**	0.030***	0.042***
	(2.690)	(2.240)	(2.710)	(3.120)
Political stability and absence of	-0.055***	-0.055**	-0.070***	-0.047**
violence and terrorism	(-3.280)	(-2.250)	(-4.650)	(-2.550)
GDP growth rate	-0.002	-0.002	0.000	0.006***
	(-1.610)	(-1.540)	(-0.040)	(4.860)
Inflation rate	0.000*	0.0001	0.000***	0.000
	(1.720)	(0.320)	(2.730)	(0.720)
Human development index	-0.654***	-0.654***	-0.504***	-0.723***
	(-3.820)	(-2.650)	(-3.140)	(-3.810)
Compliance with judiciary	0.010	0.0102	-0.034	0.070
	(0.160)	(0.130)	(-0.630)	(1.000)
Regulatory quality	-0.012	-0.0120	-0.000	-0.019
	(-0.57)	(-0.380)	(-0.030)	(-0.820)
Absence of corruption	-0.148*	-0.148	-0.077	-0.158*
	(-1.74)	(-1.250)	(-1.040)	(-1.760)
Network readiness	0.013***	0.013***	0.010***	0.012***
	(8.500)	(5.850)	(7.130)	(7.420)
Crime index	0.002***	0.002***	0.0009***	0.001*
	(3.000)	(2.980)	(1.150)	(1.960)
Complaint	-0.036	-0.036	-0.042*	-0.036
*	(-1.430)	(-1.560)	(-1.930)	(-1.340)
Largely-complaint	-0.028	-0.028	-0.024	-0.036*
	(-1.520)	(-1.560)	(-1.530)	(-1.760)
Not-complaint	0.052*	0.052	0.062***	0.059**
- -	(1.850)	(1.010)	(2.630)	(2.020)
Constant	-0.218	-0.218	-0.118	-0.201
	(-1.330)	(-1.060)	(-0.840)	(-1.120)
Region fixed effect			Yes	
Year fixed effect			Yes	
Observation	435	435	435	321
Adjusted R-Squared	0.253	0.253	0.500	0.309
F-Statistics	12.310***		12.710***	12.030***
Tolerance (VIF)	3 490			3 620
Breusch_Pagan/Cook_Weisherg test	150 170***			166 720***
breusch-Pagan/Cook-weisberg test	130.170			100.720***

Table 2. Financial crime risk and cryptocurrency adoption

The table presents the regression results of cryptocurrency adoption and ML/TF risk, along with other control variables. Column 1 presents the OLS regression; Column 2 presents the OLS regression with clustered robust error (Clustering- Country); Column 3 presents the regional fixed effect; Column 4 presents the regression results with lagged variables. The superscripts * ** , **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Established that financial crime risk drives cryptocurrency adoption across countries. We now investigate which aspects of the ML/TF risk are the most impactful. Table 3A in the Online Appendix presents the effect of different ML/TF risk proxies on cryptocurrency adoption. Panel A reveals that the Quality of the AML/CFT framework risk has a positive coefficient (0.027) and is statistically significant, implying that countries with less effective AML/CFT regulations might be more inclined to adopt cryptocurrencies, possibly because of their less stringent regulatory frameworks. This finding is also economically meaningful. In particular, an increase of one standard deviation in the quality-associated risk of the AML/CFT framework

increases cryptocurrency adoption by 19.15% [0.027*(1.121/0.158)]. Our findings reinforce the argument that the quality and adequacy of AML regulation are crucial for managing cryptocurrency activities (Lindsay, 2023). Consistent with Alnasaa et al. (2022), our evidence further emphasizes the need to enhance the quality of the AML regulatory framework to address challenges posed by cryptocurrency misuse. However, in Panels B - E, the coefficients of other ML/TF risk proxies, including bribery and corruption risk, financial transparency and standards risk, public transparency and accountability risk, and legal and political risk, are insignificant, suggesting that these risks do not significantly affect cryptocurrency adoption. Our findings offer policy implication that enhancing AML/CFT frameworks could be a particularly effective strategy for preventing the exploitation of cryptocurrency adoption for illicit activities. Moreover, given that 65% of the ML/TF risk measure is based on the quality of the AML/CFT framework, the result also provides robustness to baseline results.

3.3 Financial crime risk and cryptocurrency- stock correlations

Table 3 presents the effect of ML/TF risk on the country-level cryptocurrency-stock correlation with Bitcoin and Ethereum employed one at a time. Overall, we observe a significant negative effect of ML/TF risk on the time-varying correlation, with the largest negative effects observed in the case of Ethereum followed by Bitcoin, implied by the negative and highly significant coefficient of 0.049 on Bitcoin and 0.148 on Ethereum. The result suggests that countries with increased ML/TF risk will lead to a negative comovement between stock and equities, implying that cryptocurrency exhibits an effective diversifier in economies with financial crime risk.

Aligned with the argument that cryptocurrency, as a medium of exchange, attracts potential users due to its utility in facilitating illicit activities, and its success is ultimately contingent on maintaining a balance between its potential users and its appeal to investors (Baur et al., 2018). We find that countries with increased financial crime risk lead to a negative correlation between cryptocurrency and stock, creating an effective diversifier tool for the investor. The results contribute to the existing literature (Bao et al., 2022; Bouri et al., 2017; Dwita Mariana et al., 2021; Dyhrberg, 2016) on cryptocurrency-stock correlations by presenting evidence that ML/TF risk factors play a significant role in shaping these correlations. This implies that cryptocurrency acts as an effective diversifier in countries with higher financial crime risk. However, regulatory scrutiny and reputation risk involved in such activities could potentially undermine their appeal as a stable and legitimate investment asset. To ensure the robustness of the result, we conducted regional fixed effect and one-year lagged value regression for independent and control variables. Table A2 in the Appendix shows that the results remain consistent with the baseline model.

	Bitcoin-Stock	Bitcoin-Stock	Ethereum-Stock	Ethereum-Stock
	(DCCit)	(DCCit)	(DCCit)	(DCCit)
MLTF Risk	-0.049***	-0.049***	-0.148***	-0.148***
	(-3.670)	(-3.600)	(-5.580)	(-5.570)
Exchange rate	0.000	0.000	0.000	0.000
	(0.210)	(0.050)	(0.270)	(0.070)
Central Policy Rate	002	-0.002**	-0.005	-0.005
	(-1.020)	(-0.340)	(-1.620)	(-0.560)
GDP	.007**	0.007	0.011*	0.011**
	(2.150)	(2.220)	(1.720)	(2.050)
Inflation Rate	0.000	0.000	0.001	0.001
	(0.360)	(0.030)	(0.451)	(0.863)
GEPU	0.002***	0.002***	0.001**	.001
	(11.230)	(10.070)	(0.027)	(2.910)
MSCI WVTI	-0.007***	-0.007***	0120***	-0.012***
	(-6.600)	(-6.180)	(-7.70)	(-9.00)
Constant	-0.054	-0.054	0.838***	0.838***
	(-0.630)	(-0.720)	(3.830)	(4.850)
Observation	783	783	386	386
Adjusted R-Squared	0.208	0.208	0.215	0.215
F-Statistics	30.35		16.11	
Tolerance (VIF)	1.47		1.57	
Breusch– Pagan/Cook– Weisberg test	12.01***		1.60	

Table 3. Financial crime risk and cryptocurrency- stock correlations

The table presents the regression results of cryptocurrency adoption and ML/TF risk, along with other control variables. Column 1 presents the OLS regression; Column 2 presents the OLS regression with clustered robust error (Clustering- Country); Column 3 presents the regional fixed effect; Column 4 presents the regression results with lagged variables. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Conclusion

Using cross-country panel data, we investigate whether financial crime risk due to money laundering and terrorist financing influences cryptocurrency adoption, as well as its impact on the cryptocurrency-stock correlations. We find evidence that cryptocurrency adoption tends to be higher in countries with increased money laundering and terrorist financing risk, suggesting that financial crime risk stimulates cryptocurrency usage. We also employed an additional test to understand which subcomponents of ML/TF risk drive the baseline association. Interestingly, our findings indicate that deficiencies in the quality of AML/CFT frameworks are crucial contributing factors for cryptocurrency adoption. Our research contributes to the understanding of how cryptocurrency has been exploited for activities like money laundering and terrorist financing. The analysis also highlights the importance of effective regulatory oversights in reducing the misuse of cryptocurrencies. Thus, our study not only reaffirms the connection between cryptocurrency and illegal transactions but also highlights the critical role of regulatory oversight in influencing this relationship.

Given these insights, we also investigated the effect of financial crime risk on stock cryptocurrency. The results show a significant negative effect, indicating that cryptocurrencies (Bitcoin and Ethereum) tend to have a negative correlation with stocks in countries with higher financial crime risk. This suggests that cryptocurrencies act as effective diversifiers in these economies. However, while cryptocurrencies provide diversification benefits in high-risk environments, the associated regulatory and reputational risks may diminish their appeal as stable investment assets. Our findings remain consistent across various robustness tests, further supporting the reliability of these results.

Appendix

Table 1B	Definition	of	first	phase	variables
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Variables	Definition
Dependent variable	
Cryptocurrency adoption index	The measure of cryptocurrency deployment in a country based on chain and real-world data which normalized on a scale 0-1 using min-max method
Independent variable	
ML/TF risk index	Basel AML index measures the risk of money laundering and terrorism financing based on the AML frameworks which is then converted into a index through a calculation method of weighted scores from each domain
Control variables	
Political stability and absence of violence/terrorism	It measures the perception of the probability of political instability or violence, and terrorism caused with political motivation and provides an appropriate score in units of standard normal distribution
GDP growth rate	Weighted average of annual percentage growth rate of gross value adde by all households in the economy plus any product at market prices based on the constant local currency.
Inflation rate	Annual percent change in the overall increase in prices or increase in th cost of living in country.
Human development index	HDI is a composite measure made up of life expectancy, education and per capita income
Compliance with judiciary	It is a part of the global state of democracy indices which denotes how frequently its is assessed that government complies with the judiciary.
Regulatory quality	A measure of the ability of the government to develop and execute effective policies and regulations that permits and promotes the private sector development.
Absence of corruption	An estimation denotes the extent to which the executives and administrators do not abuse the public office for personal benefits.
Network readiness	An index which measure the potential of a country to take the advantag put forwards by information communication and technology
Crime index	A measure which signifies the overall level of crime in each country based on the perception of crime level, safety, property crimes and violent crimes
FATF recommendation-15	FATF recommendation 15 New technologies emphasize how critical it for governments to meet their commitments to implement the AML/CF standard for the virtual asset sector. Based on the evaluation reports of FATF for each country are categorized under four categories: Complain(C): Compliant, Largely complaint (LC): There are only mind shortcomings, Partially compliant(PC): There are moderate shortcomings, and Non-compliant (NC): There are major shortcomings

Table 1B	Definition	of second	phase	variables

Variables	Definition
Dependent variable	
Bitcoin-stock returns correlation	The movement between the Bitcoin and equity returns are been estimated by tin varying measure of correlation based on the dynamic conditional correlation model Engle(2002) ,utilizing the daily data spanning from 01-Jan 2012 till 31-12-2023 order to improve the estimated parameters

Ethereum-stock returns correlation	The movement between the Ethereum and equity returns are been estimated by time- varying measure of correlation based on the dynamic conditional correlation model of Engle(2002) ,utilizing the daily data spanning from 01-Jan 2018 till 31-12-2023 in order to improve the estimated parameters
Independent variable	
ML/TF risk index	Basel AML Index measures the risk of money laundering and terrorism financing based on the AML frameworks which is then converted into an index through a calculation method of weighted scores from each domain
Control Variable	
GDP growth rate	Weighted average of annual percentage growth rate of gross value added by all households in the economy plus any product at market prices based on the constant local currency.
Inflation rate	Annual percent change in the overall increase in prices or increase in the cost of living in country.
Exchange rate	An annual average of exchange rate determined by national authorities or to the rate specified in the legally sanctioned exchange market based on the monthly average (local currency units relative to the U.S. dollar). A logarithm of the exchange rate has been used to provide an intuitive measure of relative change
Central policy rate	A policy instrument that is used by central bank to implement or signal its monetary policy stance
MSCI world volatility tilt index	A measure that reflects a low-volatility strategy and high investment capacity estimated by tilting the market capitalization weights of all large and mid-cap stocks across the 23 countries on the inverse securities price variance and re-weighting them
Global economic policy uncertainty	An index that estimates the GDP-weighted average of national economic policy uncertainty indices for 21 countries.

Table 2A Descriptive	e Statistics for first phase
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Variable	Mean	Std. Dev.	Min	Max	p1	p99
Cryptocurrency adoption score	0.111	0.158	0.000	1.000	0.000	0.799
MLTF risk	5.307	1.121	2.340	8.490	3.000	8.160
Bribery and corruption risk	4.896	1.192	2.320	6.710	2.550	6.710
Quality of AMLCFT risk	5.604	0.839	4.450	7.050	4.450	7.050
Financial transparency and standard risk	4.876	1.031	2.720	6.300	2.720	6.300
Public transparency and accountability	3.995	1.065	1.330	5.790	1.930	5.790
Legal and political risk	4.414	1.077	2.230	5.820	2.310	5.820
Political stability and absence of	-0.150	0.936	-2.800	1.460	-2.580	1.315
violence/terrorism						
GDP growth rate	2.151	8.451	-54.300	80.500	-23.500	23.500
Inflation rate	18.014	121.837	-2.600	2355.100	-1.600	186.500
Human development index	0.750	0.142	0.393	0.967	0.409	0.963
Compliance with judiciary	0.582	0.206	0.010	0.960	0.120	0.950
Regulatory quality	0.066	0.961	-2.270	2.230	-2.050	1.890
Absence of corruption	0.501	0.201	0.000	1.000	0.090	0.940
Network readiness	51.603	14.909	16.600	82.750	23.340	81.370
Crime index	45.096	15.169	11.900	84.500	15.100	81.550
Compliant	0.099	0.299	0.000	1.000	0.000	1.000

Largely compliant	0.222	0.416	0.000	1.000	0.000	1.000
Non-compliant	0.146	0.353	0.000	1.000	0.000	1.000
Partially compliant	0.408	0.492	0.000	1.000	0.000	1.000
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The table shows the summary statistics of our sample for 114 countries from 2020 to 2023, including the mean, standard deviation, minimum, and maximum values.

Table 2B	Descriptive	Statistics for	or second	phase
	4			

Variables	Mean	Std.Dev.	Min	Median	Max
Bitcoin-stock returns correlation	0.09	0.39	-1.12	0.06	1.63
Ethereum-stock returns correlation	0.35	0.53	-0.96	0.31	2.29
ML/TF risk index	5.06	1.06	1.78	5.01	8.49
Exchange rate	2.24	2.61	-1.27	1.43	10.05
Central policy rate	4.45	9.97	-0.75	2.50	170.29
GDP growth rate	2.48	3.93	-29.10	2.70	24.50
Inflation rate	6.58	32.56	-3.80	2.50	667.40
GEPU	197.79	64.59	106.38	184.42	320.89
MSCIWVTI	11.34	12.67	-15.30	12.90	27.95

The table shows the summary statistics of our sample for 72 countries from 2012 to 2023, including the mean, standard deviation, minimum, and maximum values.

	(1)	(2)
Panel A- Quality of AML/CFT framework		
Quality of AML/CFT risk	0.027**	0.027**
	(2.010)	(2.040)
Constant	-0.142	-0.142
	(-0.850)	(-0.64)
Controls	Yes	Yes
Observation	435	435
Adjusted R-Squared	0.247	0.269
F-Statistics	11.970***	7.610***
Tolerance (VIF)	3.410	
Breusch-Pagan/Cook-Weisberg test	146.09***	
Panel B - Bribery and corruption risk		
	(1)	(2)
Bribery and corruption risk	-0.009	-0.009
	(-0.960)	(-0.840)
Constant	0.186	0.186
	(1.430)	(1.070)
Controls	Yes	Yes
Observation	435	435
Adjusted R-Squared	0.241	0.264
F-Statistics	11.650***	7.720***
Tolerance (VIF)	3.450	
Breusch-Pagan/Cook-Weisberg test	138.95***	
Panel C - Financial transparency and standards risk		
	(1)	(2)
Financial Transparency and standards risk	0.012	0.012
	(1.050)	(1.060)
Constant	0.030	0.030
	(0.220)	(0.180)
Observation	435	435
Controls	Yes	Yes

Table 3A. Additional analysis of ML/TF risk components

Adjusted R-Squared	0.242	0.264
F-Statistics	11.670***	8.050***
Tolerance (VIF)	3.340	
Breusch-Pagan/Cook-Weisberg test	145.11***	
Panel D- Public transparency and accountability risk		
A _ Z _ Z	(1)	(2)
Public transparency and accountability risk	-0.004	0.012
	(-0.410)	(1.060)
Constant	0.140	0.030
	(1.130)	(0.180)
Observation	435	435
Controls	Yes	Yes
Adjusted R-Squared	0.240	0.264
F-Statistics	11.570***	8.050***
Tolerance (VIF)	3.29	
Breusch-Pagan/Cook-Weisberg test	140.80***	
Panel E- Legal and political risk		
	(1)	(2)
Legal and Political risk	-0.014	-0.014
	(-1.350)	(-1.060)
Constant	0.204	0.204
	(1.620)	(1.140)
Observation	435	435
Controls	Yes	Yes
Adjusted R-Squared	0.243	0.266
F-Statistics	11.740***	7.740***
Tolerance (VIF)	3.460	
Breusch-Pagan/Cook-Weisberg test	138.71***	

The table presents the regression results of cryptocurrency adoption and ML/TF risk proxies, along with other control variables. Column 1 presents the OLS regression and Column 2 presents the OLS regression with clustered robust error (Clustering- Country). The superscripts * **, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

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