The Dark Side of the Coin: How Cryptocurrency Adoption Relates to Crime

Sofija Kaluderovic

Department of Economics and Finance, John Cabot University

EC 480 Research Seminar in Economics and Finance

Professor Adrian Stoian

April 29th, 2025

Abstract

Cryptocurrencies have gained popularity for offering decentralized, fast, and private financial transactions. However, their use has also expanded into illicit markets where anonymity is crucial. This research explores whether the rate of cryptocurrency adoption in a country is associated with crime rates. Using cross-country data from 2023, the study applies OLS regressions to test the relationship between crypto adoption and both overall and specific types of crime, controlling for macroeconomic factors. Results show a strong positive correlation between cryptocurrency adoption and crime across most categories. Law enforcement appears as a key factor linked to lower crime levels. A bidirectional analysis shows that a higher crime rate may also drive crypto adoption, suggesting a complex two-way relationship. A robustness check confirms the model's consistency over years.

Keywords:

Cryptocurrency, Crime, Crypto Adoption, Law Enforcement, Illicit Markets, Cross-Country Analysis, Darknet, Dark Web, Black Markets

JEL Classification Codes

C21 – Cross-Sectional Models; Spatial Models; Treatment Effect Models; Quantile Regressions

K42 – Illegal Behavior and the Enforcement of Law

G28 – Financial Institutions and Services: Government Policy and Regulation

O17 – Formal and Informal Sectors; Shadow Economy; Institutional Arrangements

Table of Contents

The Dark Side of the Coin: How Cryptocurrency Adoption Relates to Crime

Introduction

Since the first development of cryptocurrency, people have been drawn to it for its digital privacy and decentralized nature. The financial crisis that struck in 2008 decreased public trust in banks and other financial institutions, creating a demand for a new solution. At the time, a decentralized alternative to traditional fiat currencies seemed more attractive than ever. This is where Satoshi Nakamoto, the creator(s) of Bitcoin, drew inspiration to release a digital currency that soon became a popular store of value and investment tool.

While Bitcoin and other cryptocurrencies are often used for legitimate purposes, they also have a darker side. Hermans et al. (2022) argue, "Crypto-assets lack intrinsic economic value or reference assets, while their frequent use as an instrument of speculation, their high volatility and energy consumption, and their use in financing illicit activities make crypto-assets highly risky instruments." Originally intended to offer a simpler, faster, and cheaper means of payment for everyday transactions, cryptocurrencies quickly began attracting not only law-abiding users but also criminals. The only information recorded on the public ledger (the blockchain) about cryptocurrency transactions is the transaction amount and the wallet ID. This keeps the users' real identities private. Although transactions can sometimes be traced through blockchain analysis, it is difficult to link a wallet address to a real-world person without additional information.

Silk Road, launched in 2011, was the first widely known darknet marketplace where Bitcoin was used for transactions. After the FBI shut it down in 2013, the value of Bitcoin briefly dropped, reflecting the loss of one of its main platforms for practical use. With the emergence of privacy coins like Monero, launched in 2014, it became even harder to trace transactions, as these coins are designed to hide transaction details entirely, providing anonymity to their users. A detailed overview of various cryptocurrencies and their characteristics is provided in the European Parliament's (2018) report (p. 51).

Today, cryptocurrencies are used not only as a store of value and for fast online payments but also in illicit markets where anonymity is crucial. According to Akartuna et al. (2021), the technical complexity, decentralized structure, anonymity features, and ability to facilitate cross-border transactions make cryptocurrencies particularly attractive for criminal activities, while also complicating regulatory and law enforcement efforts. Consequently, there is growing concern among policymakers and governments about the potential role of cryptocurrencies in facilitating crime.

This research explores whether the rate of cryptocurrency adoption in a country affects the overall crime rate and specific types of crime while controlling for relevant macroeconomic factors. The research hypothesis is that countries with higher levels of crypto adoption will experience higher levels of crime.

Literature Review

The link between cryptocurrency and criminal activity has received growing attention in recent years, but many studies focus either on conceptual or legal challenges without offering broad empirical analysis across countries. For instance, Kethineni and Cao (2020) discuss how features like anonymity and decentralization make cryptocurrencies attractive for illicit uses such as drug trafficking, money laundering, and extortion. Their paper highlights regulatory struggles, especially across borders, and calls for stronger international cooperation. However, it mainly emphasizes legal and enforcement challenges rather than quantifying the relationship between crypto adoption and crime at the country level.

Khan et al. (2024) provide a systematic review of 45 papers on crypto-related crimes. They explore a wide range of illicit activities involving Bitcoin and point out the major weaknesses in existing law enforcement strategies. Some of the more innovative solutions they discuss include using machine learning to detect abnormal transaction patterns. While useful, the study remains conceptual and does not offer a model that examines actual national-level data on crime and crypto adoption.

A step closer to that kind of approach is the paper by Kovalchuk et al. (2024), which is one of the few studies attempting to model crypto-related crime using country-level data. They use correspondence analysis to explore associations between factors like GDP, digital development, cybersecurity, and cryptocurrency-related fraud. Their findings suggest that crypto crime is more common in countries with higher digital development and lower cybersecurity. However, the paper mostly focuses on fraud and cybersecurity and does not examine different types of crime. It also fails to measure the strength of the association between cryptocurrency adoption and crime, as it treats the variables as categorical and does not quantify the strength of their relationship.

Dupuis and Gleason (2021) look at how cryptocurrencies are used for money laundering. They apply the regulatory dialectic model to explain how criminals innovate around new regulations. They identify six key "open doors" through which funds are laundered using cryptocurrency, including privacy coins, decentralized exchanges, and tumblers. While the paper highlights important techniques and regulatory shortcomings, it is conceptual and does not test any empirical relationship between crime and crypto use.

Europol (2022)'s Spotlight report highlights that, according to Chainalysis, illicit transactions accounted for only 0.34% of all cryptocurrency activity in 2020 (p. 4). However, the same report also references academic research by Foley et al. (2019) estimating that approximately 23% of Bitcoin transactions are associated with criminal activities (p. 5). Therefore, it remains debatable to what extent cryptocurrency usage is oriented toward criminal activities.

What is still missing in this literature is a broad, country-level empirical analysis of whether cryptocurrency adoption is associated with higher crime rates and how this relationship might vary across different types of crime. My research contributes to filling this gap. By gathering data from 2023 and applying a consistent OLS regression model, the paper tests whether crypto adoption has a statistically significant effect on crime. Additionally, unlike previous work, this study also checks the reverse relationship—whether crime affects crypto adoption—something that is not talked about as much.

Data Description

The Global Crypto Adoption Index in this study is taken from Chainalysis (2023). Chainalysis is a leading blockchain data platform. It provides data, software, services, and research to governments, financial institutions, and insurance and cybersecurity companies in over 70 countries. In order to calculate the cryptocurrency adoption index, the organization uses four sub-indexes:

1. on-chain cryptocurrency value received by centralized services,
2. on-chain retail cryptocurrency value received by centralized services,
3. on-chain cryptocurrency value received by DeFi protocols,
4. on-chain retail cryptocurrency value received by DeFi protocols

all weighted by GDP per capita on a PPP-adjusted basis. It takes the geometric mean of each country’s ranking in all four and then normalizes that final number on a scale of 0 to 1. The

Global Crypto Adoption Index is calculated each year starting from 2020. This research primarily uses the 2023 Global Crypto Adoption Index but also incorporates 2021 data to test the model's applicability over time.

The crime rates in this research are developed by the Global Initiative Against Transnational Organized Crime (2023). The index is published every two years and is supported by the ENACT project, which is funded by the European Union and implemented in partnership with INTERPOL and the Institute for Security Studies (ISS). While the organization calculates the overall criminality index for each country, it also provides separate indexes for different crime categories, including human trafficking, arms trafficking, flora, fauna, and non-renewable resource crimes, various drug trades, cybercrimes, financial crimes, and criminal networks. In addition, it calculates the government transparency and accountability index, as well as the law enforcement index, for each country. This research will use some of these indexes, primarily from 2023, along with data from 2021.

Most of the control variables were obtained from the World Bank Group, including GDP per capita (in current US dollars), unemployment rate, inflation rate (using the Consumer Price Index as a proxy), and the percentage of the population using the Internet (World Bank, n.d.-b; World Bank, n.d.-d; World Bank, n.d.-a; World Bank, n.d.-c). The data from 2021 and 2023 were used.

Finally, this research includes an inequality index as a control variable, taken from the World Inequality Lab (n.d.). Specifically, it uses the share of a country’s wealth owned by the top 10% of the population as a proxy for inequality. Data from both 2023 and 2021 were used.

Table 1 displays summary statistics for all variables included in the dataset. Each variable has 147 observations, so there are no missing values. The independent variable — the Crypto

Adoption Index — ranges from 0 to 1, with a mean of 0.0447 and a standard deviation of 0.116. This suggests that most observations are clustered on the left (closer to 0), with only a few countries having higher adoption levels (closer to 1). Given this skewed distribution, the model might benefit from a transformation of the independent variable.

Criminality rates represent the level of various types of crime in a country, measured on a scale from 1 to 10. Different crime categories have different ranges within the dataset. The Overall Crime Index, for instance, ranges from 2.82 to 8.15.

There are seven control variables in the dataset:

1. GDP per Capita, ranging from 415.7 to 128,678 USD;
2. Unemployment Rate, ranging from 0.13% to 32.1%;
3. Inequality Index, ranging from 0.28 to 0.654, where a value of 1 would indicate that 100% of a country’s wealth is owned by the richest 10% of the population;
4. Inflation Rate, with a minimum of -7.71 and a maximum of 667.4;
5. Government Transparency, ranging from 1 to 9, with 1 indicating a lack of transparency and 9 indicating high transparency;
6. Law Enforcement, ranging from 1.5 to 9, with lower values indicating weaker law enforcement in a country;
7. Internet users, ranging from 15.3% to 100%.

Methodology

The paper applies ordinary least squares (OLS) regression to examine the relationship between cryptocurrency adoption and crime rates across countries in 2023. The main model tested whether crypto adoption was associated with overall crime, controlling for key macroeconomic variables. The Crypto Adoption Index was used in the model instead of the

Crypto Adoption Ranking, as the coefficient associated with the latter could not be meaningfully interpreted. Specifically, the Crypto Adoption Ranking would only reflect the effect of a country moving up or down by one position in the ranking, without reflecting the scale of change in actual crypto adoption. While the Crypto Adoption Index is not meaningful in absolute terms, it reflects a country's intensity of cryptocurrency adoption relative to the top-ranked country (which has a normalized score of 1). This enables a more informative comparison on a relative scale.

A bidirectional approach was applied to explore whether overall crime level influences crypto adoption. Separate regressions were run for eight specific crime categories to investigate variation across different types of crime. Finally, a robustness check using 2021 data was performed to assess the applicability of the model over time.

Table 2 presents results from the initial OLS regression, using the Overall Crime Index as the dependent variable. The model has an R-squared of 0.44, indicating that it explains 44% of the variation in the dependent variable. Although this is the preliminary model without further modifications, two variables emerge as statistically significant at the 1% level: Crypto Adoption Index and Law Enforcement. The results suggest that, holding everything else constant, a 1-point increase in the Crypto Adoption Index is associated with an average increase of 2.513 points in the Overall Crime Index. This is a substantial effect, especially considering that the criminality score is based on a 1 to 10 scale. As expected, higher law enforcement is associated with lower crime. The results suggest that, holding everything else constant, a 1-point increase in Law Enforcement is associated with an average decrease of 0.313 points in the Overall Crime Index. This is also a substantial effect, as both Law Enforcement and the dependent variable are based on a 1 to 10 scale.

To assess potential multicollinearity among the independent variables, a correlation matrix was generated, as shown in *Table 3*. The most notable value is 0.8089, which is the correlation between the Government Transparency and Law Enforcement variables. Due to this high correlation, the Government Transparency variable was excluded from subsequent regressions. There is also a relatively strong correlation between Law Enforcement and GDP per Capita (0.6724). However, it was not considered high enough to be a serious concern.

Next, to improve the model, the research focused on possible variable transformations. To better assess the room for improvement, scatter plots were generated to evaluate whether the independent variables in their raw form showed a linear relationship with the Overall Crime Index. While some control variables displayed a nonlinear pattern — such as Unemployment Rate, Inflation Rate, and GDP per capita — their transformation did not lead to any significant improvement in the model or make them statistically significant. Therefore, the control variables were kept in their original form.

Figure 1 displays the scatter plot of the Overall Crime Index against the Crypto Adoption Index. What immediately stands out is the uneven distribution of the independent variable, as previously noted in the Data Description section. Most observations are clustered very close to 0, with only a few countries standing out. This is expected, given that the Crypto Adoption Index is a normalized measure that assigns a score to each country relative to others. As some countries have a much higher degree of cryptocurrency adoption, they appear as clear outliers. In 2023, India received the maximum score of 1, followed by Nigeria, Vietnam, and the USA. To bring the data points closer together and reduce the spread, applying the natural logarithm transformation to the Crypto Adoption Index appeared to be a reasonable solution. Since the natural logarithm of 0 is undefined, a new independent variable was generated using the formula log(CryptoAdoptionIndex + 0.01), where 0.01 is a small constant added to allow for the transformation. This adjustment was necessary because of the large number of observations with a Crypto Adoption Index of 0.

Table 4 displays the results of the OLS regression with the transformed independent variable. As shown, the new independent variable, logCryptoAdoption, is significant at the 1% level. The only other significant variable, also at the 1% level, remains Law Enforcement. This updated model has an R-squared of 0.55, which is higher than the first model's R-squared of 0.44. These results suggest that transforming the independent variable improved the model's overall performance, so the log version of the index was used in all subsequent regressions.

To further assess the new model's performance, a residual plot was generated, as displayed in *Figure 2*. The residuals do not display any clear pattern or shape, and their variance appears roughly constant across all fitted values. Most of the residuals are centered on 0 and fall within the range of -2 to 2. These characteristics suggest that the model meets key OLS assumptions, such as linearity and homoscedasticity. However, there is one visible outlier below -2, which corresponds to Antigua and Barbuda. Since this island nation may be an outlier due to its small size and unique characteristics, it will be excluded from the final model to avoid its influence on the results.

Results

Table 5 presents the results of the final regression based on 146 observations. The model has an R-squared of 0.561, the highest among all models discussed in the Methodology section. Two variables are significant at the 1% level: the Crypto Adoption Index and Law Enforcement.

The results suggest that, holding everything else constant, a 1% increase in the Crypto Adoption Index is associated with an average increase of 0.00513 points in the Overall Crime

Index. This means that a 100% increase in the index (e.g., from 0.5 to 1) would correspond to an average rise of 0.513 in the crime score. For instance, if Vietnam's crypto adoption score, which was close to 0.5 in 2023, increased to match India's score of 1, its predicted crime rate would rise by approximately 0.513, holding everything else constant. This is a substantial change, especially considering that the Overall Crime Index is calculated on a scale from 1 to 10.

The coefficient corresponding to the other significant variable, Law Enforcement, suggests that, holding everything else constant, a one-point increase in the Law Enforcement index is associated with an average decrease of 0.423 in the Overall Crime Index. This is also a meaningful change, implying that countries that have a better law enforcement mechanism tend to experience lower levels of crime.

Next, eight separate regressions were run to assess the effect of cryptocurrency adoption on different types of crime. The same model was applied to all crime categories for consistency and comparison. *Table 6* displays the results of the OLS regressions run with Criminal Markets, Human Trafficking, Arms Trafficking, and Non-renewable Resource Crimes as dependent variables.

The Crypto Adoption Index proved to be significant for all four types of crime at the 1% level. The coefficients corresponding to the Crypto Adoption Index have notable magnitudes in all four models, with the largest effects observed in Arms Trafficking and Non-renewable Resource Crimes. This highlights the role cryptocurrency may play in facilitating these serious, organized types of crime.

Law Enforcement is significant at the 1% level in all four models as well, showing a consistent negative relationship with crime. This suggests that stronger law enforcement capacity is associated with lower levels of these crimes.

Interestingly, different control variables are significant for different crime categories. In particular, the Inequality Index is significant at the 1% level for Non-renewable Resource Crimes and at the 5% level for Criminal Markets, both with a positive coefficient as expected. The Unemployment Rate is significant at the 5% level for Human Trafficking. However, the model suggests that unemployment has a negative effect on human trafficking levels, which is somewhat surprising. The magnitude of this relationship is not great, so this might indicate a rather weak effect, or it can be the result of other confounding factors.

Finally, GDP per Capita appears significant for Arms Trafficking at the 1% level and for Non-renewable Resource Crimes at the 10% level. This suggests that economic factors might play a role in shaping the conditions under which certain crimes, such as these two types of crime, occur.

Just as *Table 6* does, *Table 7* displays regression outputs for four different crime categories: Heroin Trade, Cocaine Trade, Cannabis Trade, and Criminal Actors. The Crypto Adoption Index was significant for Heroin Trade and Criminal Actors at the 1% level, with coefficients of similar magnitude to those observed in the previous regressions.

However, the Cocaine Trade and Cannabis Trade models stand out. In the former, the Crypto Adoption Index is not statistically significant, while in the latter, it is significant at the 10% level but has a considerably smaller coefficient compared to other crime categories. Furthermore, the R-squared values for the three models with drug-related crimes as the dependent variable are substantially lower than those of the other models. While the R-squared for the remaining regressions does not fall below 0.4, the values for these three models are 0.124, 0.065, and 0.108, indicating that the variation in the dependent variable is only weakly explained by the model. A possible explanation might be that drug trafficking often relies more heavily on physical distribution networks and street-level operations rather than on black markets where cryptocurrencies are the predominant method of payment. Especially in the case of widespread substances like cocaine and cannabis, which are often traded by localized criminal networks, distribution may be easier to access without the use of cryptocurrencies. Cannabis is also legal in some countries, so it is not as widely sought after on black markets globally.

Interestingly, Law Enforcement is not significant in three out of the four regressions in *Table 7*, suggesting that drug trade may not be strongly affected by a country's law enforcement capacity. In some countries, drug trading may be so embedded in the system that it is not actively opposed, or even indirectly supported, by government institutions, which could explain these results. On the other hand, Law Enforcement is significant at the 1% level for Criminal Actors and in all the regression outputs in *Table 6*, suggesting that law enforcement still plays a key role in regulating these forms of organized crime.

Finally, the Inequality Index is significant at the 5% level for Cocaine Trade, suggesting that, on average, countries with higher inequality tend to have higher levels of cocaine trade.

Next, the research explored whether crime levels might influence cryptocurrency adoption. It is important to examine both directions of this relationship, as previous results indicate correlation but do not establish causality. It remains unclear whether crypto adoption drives crime, crime drives crypto adoption, or whether a third factor drives both. To address this, a model was generated with the dependent and independent variables switched. *Table 8* presents the results of this regression.

The model has an R-squared of 0.349, suggesting that approximately 35% of the variation in the Crypto Adoption Index can be explained by the independent variables. The Overall Crime Index is statistically significant at the 1% level. The coefficient indicates that, holding everything else constant, a one-point increase in the Overall Crime Index is associated with an average 55.7% increase in the Crypto Adoption Index, which is a substantial change. These findings may suggest that in countries with higher crime levels, people tend to use cryptocurrencies more, potentially for both illicit and legitimate purposes.

In this model, GDP per Capita was transformed using the natural logarithm. The variable is significant at the 1% level and negatively associated with the Crypto Adoption Index. This could imply that cryptocurrency adoption is more prevalent in countries with lower levels of economic development, possibly reflecting reduced trust in domestic financial institutions or greater barriers to financial access.

The Unemployment Rate is also significant at the 1% level, with a negative coefficient. This suggests that, on average, countries with higher unemployment may experience lower levels of crypto adoption, though this relationship might be influenced by some factors not captured in the model.

Law Enforcement is significant at the 1% level with a positive coefficient, indicating that stronger law enforcement is associated with greater cryptocurrency adoption. One possible interpretation is that in countries with stronger institutional structures and legal protections, legitimate users might feel more secure using emerging technologies like cryptocurrencies.

Finally, the percentage of Internet Users is significant at the 5% level, with a positive coefficient. This aligns with expectations, as greater internet penetration logically supports higher rates of cryptocurrency use.

Overall, these results reinforce the idea that there may be a two-way relationship between cryptocurrency adoption and crime. Higher crime rates may be associated with increased crypto adoption, which could, in turn, facilitate certain types of criminal activity, creating a vicious cycle. However, further research is needed to confirm the direction and nature of this relationship.

Finally, a robustness check was conducted to test the stability of results over time, as shown in *Table 9*. For this model, data from 2021 were used with the same set of variables and methodology as the 2023 model in *Table 5*. The model yields an R-squared of 0.507, similar to the earlier model. Again, two variables are significant at the 1% level: the Crypto Adoption Index and Law Enforcement, both with similar coefficients as in the 2023 model. This consistency suggests that the model is applicable over time. While the model could be further refined by including additional control variables or adopting alternative methodological approaches, it appears to be a strong fit for this data.

Limitations

Even though this research shows significant results, it does not confirm a causal relationship between cryptocurrency adoption and crime rates. Instead, it demonstrates a strong correlation between them.

The Crypto Adoption Index is normalized, potentially reducing variation between countries. Since the index is assigned to countries relative to one another, it does not provide meaningful information in absolute terms. As a result, it was not possible to apply a model that assesses change over time, and the dataset had to be treated as cross-sectional. This cross-sectional design limits the ability to draw temporal conclusions, meaning long-term effects cannot be assessed from this research. A possible solution could be to use a different measure of cryptocurrency adoption across countries or to include an alternative variable.

Additionally, data quality and reporting standards may vary across countries. This is especially relevant for the main variables — the Crypto Adoption Index and crime rates —

where the data can be difficult to measure accurately, as they do not have a standardized unit of measurement. Therefore, the extent to which the data used in this paper reflects reality is questionable.

The dataset also does not distinguish between different types of cryptocurrency use (e.g., legal vs. illicit transactions). While cryptocurrencies can facilitate illegal activity, they are also widely used for legitimate purposes, such as a store of value.

Finally, unobserved variables (such as corruption levels or digital literacy) may influence both crypto adoption and crime rates but were not included in the model. Future research should aim to incorporate additional control variables to account for these potential influences.

Conclusions

In conclusion, this research has explored whether the rate of cryptocurrency adoption in a country affects crime rates in that country, filling in the gap of the previous literature on this topic, which is mostly theoretical. The findings suggest that crypto adoption is positively correlated with various crime rates across countries. The relationship appears bidirectional and is statistically significant in both directions. However, the model predicting crime from crypto adoption demonstrates a better fit, indicating that variation in crypto adoption may explain differences in crime rates better than the other way around.

Law enforcement appears to be a key factor associated with lower crime levels. When analyzing specific types of crime, different control variables proved significant depending on the category. Crypto adoption was significant in all but one of the crime types examined (cocaine trade). Generally, drug trafficking does not appear to depend on cryptocurrency adoption as much as other crime categories. A robustness check using data from a different year confirmed the model’s consistency and applicability over time.

These findings may carry important policy implications. Greater investment in law enforcement capacity could help reduce crime. Additionally, more targeted regulation around the use of cryptocurrencies may help limit their misuse. However, it is very important not to hinder the legitimate use of cryptocurrencies. As stated in the European Parliament (2018)’s report:

> As regards blockchain, it would be too blunt to associate blockchain with money laundering, terrorist financing or tax evasion. It is just technology, on which a large number of cryptocurrencies run, but which is not designed to launder money, facilitate terrorist financing or evade taxes. Blockchain has numerous applications throughout the whole lawful economy. It would not be wise to discourage future innovations in this respect by submitting blockchain and fintech's exploring its use cases to burdensome requirements, simply because of one of the applications using blockchain technology, cryptocurrencies, is used illicitly by some. Therefore, blockchain should be left untouched from a money laundering, terrorist financing and tax evasion perspective. The fight against money laundering, terrorist financing and tax evasion should focus on the illicit use cases of cryptocurrencies. (p. 10)

This research highlights a significant positive association between cryptocurrency adoption and criminality. However, uncovering the causal mechanisms behind this relationship will require further empirical investigation.

References

Akartuna, E. A., Hetzel, F., & Kleinberg, B. (2021, February). *Cryptocurrencies and future crime* [Policy brief]. Dawes Centre for Future Crime at UCL. https://www.ucl.ac.uk/jill-dando-institute/sites/jill-dando-institute/files/ucl_cryptocurrencies_and_future_crime_policy_briefing_feb2021_compressed_1.pdf

Chainalysis. (2023, January 12). *2023 crypto crime trends: Illicit cryptocurrency volumes reach all-time highs amid surge in sanctions designations and hacking.* https://www.chainalysis.com/blog/2023-crypto-crime-report-introduction/

Dupuis, D., & Gleason, K. (2021). Money laundering with cryptocurrency: open doors and the regulatory dialectic. *Journal of Financial Crime*, *28*(1), 60–74. https://doi.org/10.1108/JFC-06-2020-0113

European Parliament, Policy Department for Economic, Scientific and Quality of Life Policies. (2018). *Cryptocurrencies and blockchain: Legal context and implications for financial crime, money laundering and tax evasion*. Publications Office of the European Union. https://op.europa.eu/en/publication-detail/-/publication/631f847c-b4aa-11e8-99ee-01aa75ed71a1

Europol. (2022). *Cryptocurrencies: Tracing the evolution of criminal finances*. Europol Spotlight Report series. Publications Office of the European Union. https://www.europol.europa.eu/publications-events/publications/cryptocurrencies-tracing-evolution-of-criminal-finances

Global Initiative Against Transnational Organized Crime. (2023). *Global Organized Crime Index 2023: A fractured world*. https://ocindex.net/report/2023/0-3-contents.html

Hermans, L., Ianiro, A., Kochanska, U., Törmälehto, V.-M., van der Kraaij, A., & Vendrell Simón, J. M. (2022). *Decrypting financial stability risks in crypto-asset markets. Financial Stability Review*, May 2022. European Central Bank. https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202205_02~1cc6b111b4.en.html

Kethineni, S., & Cao, Y. (2020). The Rise in Popularity of Cryptocurrency and Associated Criminal Activity. *International Criminal Justice Review, 30*(3), 325–344. https://doi.org/10.1177/1057567719827051

Khan, D. D., Farman, H., Hassan, S., Seelro, M., & Mughal, M. H. (2024). Cryptocurrency Crimes: A systematic Review on Illicit activities using cryptocurrency (Bitcoin) and challenges for Law Enforcement Agencies. *Pakistan Journal of Engineering, Technology & Science, 12*(1), 12–25. https://doi.org/10.22555/pjets.v12i1.1121

Kovalchuk, O., Shevchuk, R., & Banakh, S. (2024). Cryptocurrency Crime Risks Modeling: Environment, E-Commerce, and Cybersecurity Issue. *IEEE Access, 12*, 50673–50688. https://ieeexplore.ieee.org/document/10494758

World Bank. (n.d.-a). *A global database of inflation* [Data set]. https://www.worldbank.org/en/research/brief/inflation-database

World Bank. (n.d.-b). *GDP per capita (current US$)* [Data set]. World Development Indicators. https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

World Bank. (n.d.-c). *Individuals using the Internet (% of population)* [Data set]. World Development Indicators. https://data.worldbank.org/indicator/IT.NET.USER.ZS

World Bank. (n.d. -d). *Unemployment, total (% of total labor force) (modeled ILO estimate)* [Data set]. World Development Indicators. https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS

World Inequality Lab. (n.d.). *World Inequality Database: Top 10% income share (%)* [Data set]. Retrieved February 26, 2025, from https://wid.world/world/#sptinc_p90p100_z/US;FR;DE;CN;ZA;GB;WO/2023/eu/k/p/yearly/s/false/24.722500000000004/80/curve/false/country

Appendices

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Crypto Adoption Index	147	0.0447	0.116	0	1
Crypto Adoption Ranking	147	77.8	45.22	1	155
Overall Crime Index	147	5.33	1.176	2.82	8.15
Criminal Markets	147	5.209	1.136	2.43	8.13
Human Trafficking	147	6.061	1.455	3	9
Human Smuggling	147	5.534	1.786	1.5	9.5
Arms Trafficking	147	5.456	2.08	1.5	9.5
Flora Crimes	147	4.272	2.153	1	9
Fauna Crimes	147	4.959	1.817	1.5	9
Nonrenewable Resource Crimes	147	5.061	2.414	1	9.5
Heroin Trade	147	4.588	1.991	1	9.5
Cocaine Trade	147	5.177	2.051	1	9.5
Synthetic Drug Trade	147	5.439	1.877	1	10
Criminal Actors	147	5.451	1.347	2.4	8.6
Mafia-style Groups	147	4.568	2.291	1	9.5
Criminal Networks	147	5.946	1.478	2	9.5
GDP per Capita (US$)	147	19,578	24,479	415.7	128,678
Unemployment Rate	147	6.796	5.111	0.13	32.1
Inequality Index	147	0.449	0.0888	0.28	0.654
Inflation Rate	147	16.93	61.73	-7.71	667.4
Government Transparency	147	4.534	1.924	1	9
Law Enforcement	147	5.027	1.8	1.5	9
Internet Users (% of population)	147	74.52	23.56	15.3	100

Table 1: Summary Statistics

VARIABLES	(1) OLS
CryptoAdoptionIndex	2.513***
	(0.672)
GDPperCapita	1.87e-06
	(4.60e-06)
UnemploymentRate	-0.00653
	(0.0156)
InequalityIndex	1.122
	(1.005)
InflationRate	-0.000525
	(0.00123)
GovernmentTransparency	-0.111
	(0.0682)
LawEnforcement	-0.313***
	(0.0784)
InternetUsers	0.00266
	(0.00411)
Constant	6.610***
	(0.627)
Observations	147
R-squared	0.440

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

Table 2: Initial OLS Regression (Overall Crime Index as Dependent Variable)

	Crypto~x	GDPper~a	Unempl~e	Inequa~x	Inflat~e	Govern~y	LawEnf~t	Intern~s
CryptoAdop~x	1.0000							
GDPperCapita	-0.0764	1.0000						
Unemployme~e	-0.1442	-0.2366	1.0000					
Inequality~x	0.1541	-0.4538	0.2323	1.0000				
InflationR~e	-0.0117	-0.1191	0.0421	0.1184	1.0000			
Government~y	0.0047	0.6434	-0.1727	-0.3965	-0.1427	1.0000		
LawEnforce~t	0.0107	0.6724	-0.1995	-0.4619	-0.1702	0.8089	1.0000	
InternetUs~s	-0.0596	0.5731	-0.0771	-0.3556	-0.1281	0.5128	0.5661	1.0000

Table 3: Correlation Matrix

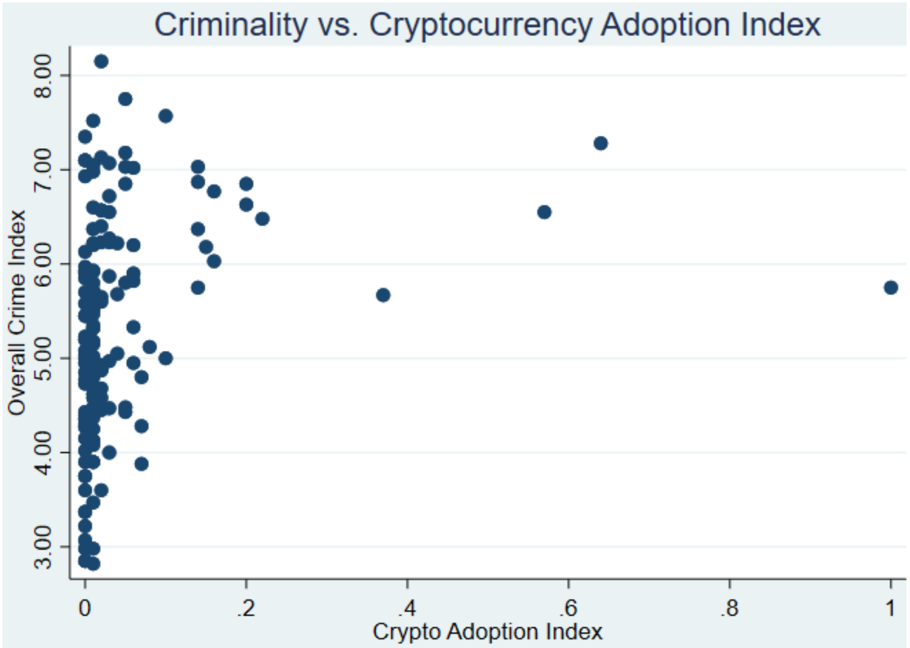

Figure 1: Scatter Plot of Overall Crime Index vs. Crypto Adoption Index

VARIABLES	(1) OLS
logCryptoAdoption	0.525***
	(0.0710)
GDPperCapita	4.63e-06
	(4.08e-06)
UnemploymentRate	0.00740
	(0.0141)
InequalityIndex	1.034
	(0.888)
InflationRate	-0.000796
	(0.00110)
LawEnforcement	-0.419***
	(0.0546)
InternetUsers	6.40e-05
	(0.00367)
Constant	8.736***
	(0.643)
Observations	147
R-squared	0.550

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

Table 4: OLS Regression with a Transformed Independent Variable (Overall Crime Index as Dependent Variable)

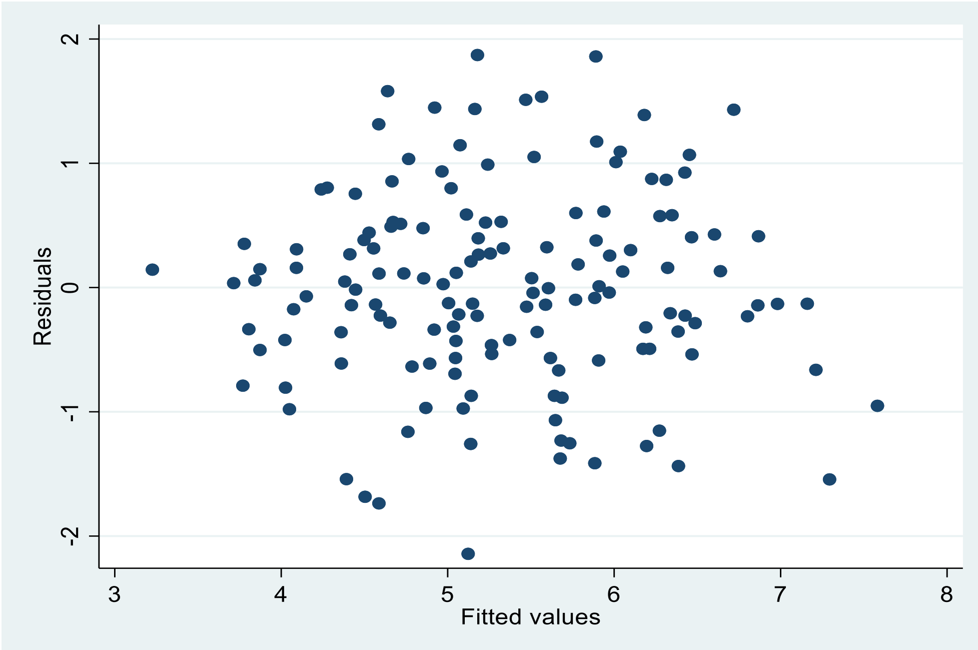

Figure 2: Residual Plot of the Improved Model

VARIABLES	(1) OLS
logCryptoAdoption	0.513***
	(0.0696)
GDPperCapita	4.94e-06
	(3.99e-06)
UnemploymentRate	0.00981
	(0.0138)
InequalityIndex	1.109
	(0.868)
InflationRate	-0.000855
	(0.00108)
LawEnforcement	-0.423***
	(0.0534)
InternetUsers	0.000246
	(0.00359)
Constant	8.656***
	(0.629)
Observations	146
R-squared	0.561

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

Table 5: Final OLS Regression

VARIABLES	(1) Criminal Markets	(2) Human Trafficking	(4) Arms Trafficking	(5) Non-renewable resource Crimes
logCryptoAdoption	0.576***	0.473***	0.619***	0.611***
	(0.0681)	(0.0957)	(0.145)	(0.155)
GDP per Capita (US$)	6.20e-06	7.20e-06	2.47e-05***	1.74e-05*
	(3.90e-06)	(5.48e-06)	(8.31e-06)	(8.86e-06)
Unemployment Rate	-0.00706	-0.0480**	0.0397	-0.00659
	(0.0135)	(0.0190)	(0.0288)	(0.0307)
Inequality Index	2.066**	1.015	2.956	6.100***
	(0.850)	(1.195)	(1.810)	(1.931)
Inflation Rate	-0.00145	-0.00221	-0.00269	0.00154
	(0.00106)	(0.00148)	(0.00225)	(0.00240)
Law Enforcement	-0.331***	-0.510***	-0.666***	-0.716***
	(0.0523)	(0.0734)	(0.111)	(0.119)
Internet Users (% of population)	-0.00177	-0.00290	-0.0142*	-0.0155*
	(0.00351)	(0.00494)	(0.00748)	(0.00798)
Constant	8.120***	10.33***	10.08***	8.983***
	(0.616)	(0.866)	(1.312)	(1.399)
Observations	146	146	146	146
R-squared	0.545	0.464	0.403	0.491

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

Table 6: OLS Regressions by Crime Type (Part 1): Effects of Cryptocurrency Adoption on Specific Crime Categories

VARIABLES	(1) Heroin Trade	(2) Cocaine Trade	(3) Cannabis Trade	(4) Criminal Actors
logCryptoAdoption	0.597***	-0.0454	0.222*	0.450***
	(0.168)	(0.179)	(0.121)	(0.0843)
GDP per Capita (US$)	-9.47e-07	1.05e-05	-1.07e-05	3.67e-06
	(9.64e-06)	(1.03e-05)	(6.93e-06)	(4.83e-06)
Unemployment Rate	-0.0216	-0.0376	-0.0176	0.0270
	(0.0334)	(0.0356)	(0.0240)	(0.0167)
Inequality Index	-0.634	5.754**	1.062	0.153
	(2.101)	(2.240)	(1.510)	(1.052)
Inflation Rate	-0.00323	0.000418	0.00261	-0.000273
	(0.00261)	(0.00278)	(0.00187)	(0.00131)
Law Enforcement	-0.210	-0.00483	-0.0275	-0.515***
	(0.129)	(0.138)	(0.0928)	(0.0647)
Internet Users (% of population)	0.00141	0.0107	0.00119	0.00222
	(0.00868)	(0.00926)	(0.00624)	(0.00435)
Constant	8.201***	1.690	6.187***	9.191***
	(1.522)	(1.623)	(1.094)	(0.762)
Observations	146	146	146	146
R-squared	0.124	0.065	0.108	0.514

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

Table 7: OLS Regressions by Crime Type (Part 2): Effects of Cryptocurrency Adoption on Specific Crime Categories

VARIABLES	(1) OLS
Overall Crime Index	0.557***
	(0.0747)
logGDPperCapita	-0.318***
	(0.121)
Unemployment Rate	-0.0385***
	(0.0139)
Inequality Index	0.498
	(0.901)
Inflation Rate	0.000836
	(0.00112)
Law Enforcement	0.320***
	(0.0641)
Internet Users (% of population)	0.0123**
	(0.00596)
Constant	-6.204***
	(0.981)
Observations	146
R-squared	0.349

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

Table 8: Reverse OLS Regression: Effect of the Overall Crime Index on Crypto Adoption Index

VARIABLES	(1) OLS
logCryptoAdoption	0.577***
	(0.0838)
GDPperCapita	-2.17e-06
	(3.27e-06)
UnemploymentRate	0.00839
	(0.0142)
InequalityIndex	1.344
	(0.907)
InflationRate	-0.000484
	(0.000556)
Lawenforcement	-0.346***
	(0.0576)
InternetUsersPercentage	0.00344
	(0.00389)
Constant	7.766***
	(0.620)
Observations	147
R-squared	0.507

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

Table 9: Robustness Check Using 2021 Data: Effect of Crypto Adoption Index on Overall Crime Index