Opting Out? Cryptocurrency Under Consideration of Currency Substitution

Degree Dissertation

Alec Vayloyan

Degree Dissertation submitted as part of the requirements for the MSc in Applied Information and Data Science at the School of Business, Lucerne University of Applied Sciences and Arts

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HSLU Hochschule Luzern

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Author: Alec Vayloyan, MSc Student Applied Information and Data Science

E-mail: vayloyanalec49@gmail.com

Matriculation Number: 23-576-119

Supervisor: Dr. Denis Bieri

Location: Room 6.03, Suurstoffi 1, 6343 Rotkreuz

E-mail: denis.bieri@hslu.ch

Co-Supervisor: Prof. Dr. Thomas Ankenbrand

Location: Room 6.01, Suurstoffi 1, 6343 Rotkreuz

E-mail: thomas.ankenbrand@hslu.ch

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Abstract

This study investigates the drivers of cryptocurrency adoption using the framework of currency substitution theory, motivated by the theoretical overlap in use cases between foreign fiat currencies and cryptocurrency. Drawing on panel data for cryptocurrency adoption from both Statista (2019-2023) and Chainalysis (robustness check, 2020-2023), the analysis evaluates the influence of currency stability, investment, wealth, illicit activities ("sins"), remittances, capital controls and sovereign default risk on cryptocurrency adoption across countries. The inclusion of sovereign default risk is a novel approach in the literature on cryptocurrency adoption. Four econometric models - using both untransformed and transformed linear regressions, as well as fixed effects - are applied.

While no predictor exhibited consistent statistical significance and direction of effect across all models, sovereign default risk exhibits the strongest evidence for an underlying relationship, being the only predictor statistically significant with the same direction of effect across two models using different measures of cryptocurrency adoption. This supports the idea that cryptocurrencies serve as currency substitution. However, currency stability, the main other predictor of currency substitution in the literature, does not exhibit a consistent direction of effect in the models tested. This weakens the evidence for cryptocurrencies' use as currency substitution. Remittances, investment and sins show a consistent direction of effect statistically significant in two models, both using the same measure of cryptocurrency adoption. The findings for these predictors align with the literature, except for remittances, which exhibit a negative relationship with adoption in the models. The proxy for capital controls was statistically insignificant in all models. The findings related to wealth were inconclusive due to differing directions of effect in models where this predictor was statistically significant.

Overall, the results indicate that while elements of currency substitution theory can explain cryptocurrency adoption, unmodeled factors also influence cryptocurrency adoption. This study contributes both to the cryptocurrency and currency substitution literature by integrating currency substitution theory into the analysis of cryptocurrency adoption.

Keywords: Cryptocurrency, Currency Substitution, Dollarization 2.0, Remittances

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List of Abbreviations

The following abbreviations were used in this paper:

AI: Artificial Intelligence

ARCH: Autoregressive Conditional Heteroscedasticity

CC: Capital Controls

CHF: Swiss Franc

ED: External Debt

GDS: Gross Domestic Savings

GDP: Gross Domestic Product

IMF: International Monetary Fund

K: Thousand

KYC: Know Your Customer

M: Million

MCAR: Missing Completely at Random

NAI: Nearest Average Imputation

RR: Remittances Received

USD: United States Dollar

Preface

I would like to express my sincere gratitude to Dr. Denis Bieri and Prof. Dr. Thomas Ankenbrand for allowing me to write this project under their guidance and for the opportunity to benefit from their vast knowledge and experience in the field of (decentralized) finance.

Secondly, I would like to thank Dr. Kristin Makszin for initially suggesting the currency substitution mechanism and encouraging me to further pursue the idea in a research design course over five years ago. She is remembered fondly by students - even years after graduation - for the time and effort she is willing to invest into students and their projects.

Finally, I would not be here without the love and support of my parents, Carmen and Arthur, as well as my *Omi*, Luise. I am truly privileged to have such an amazing family.

A reflection on the use of artificial intelligence (AI) is included at the end of this paper. It also provides credit for the cover image used (see Appendix 5).

1 Introduction and Topic Definition

The development of cryptocurrencies, spawned alongside blockchain technology, has challenged traditional monetary systems and economic structures. Since their inception in the wake of the Global Financial Crisis, cryptocurrencies have been championed by advocates for their decentralized nature, security, and potential as a replacement for fiat currencies. Cryptocurrencies are often viewed in the public narrative as a solution for individuals and nations where conventional financial systems are dysfunctional or highly volatile, providing an alternative currency that is not controlled by the same rules as a potentially suboptimal financial system. The use of alternative currencies is not a new phenomenon. There is a large body of research devoted to understanding why people choose to use foreign fiat currencies. Due to the overlap in both potential use cases and underlying conditions stimulating the use of both foreign fiat currencies and cryptocurrencies, this paper integrates the theory on the use of foreign fiat currencies into a model of cryptocurrency adoption.

Using four econometric models across two measures of cryptocurrency adoption, the analysis evaluates the influence of currency stability, investment, wealth, illicit activities ("sins"), remittances, capital controls (CC) and sovereign default risk on cryptocurrency adoption across a wide range of countries. The inclusion of sovereign default risk is novel in the cryptocurrency adoption research and is motivated by this factor's relevance in the currency substitution literature. No underlying factor showed consistent statistical significance and direction of effect across all models. The strongest evidence for an underlying relationship was in relation to the sovereign default risk. This was the only factor with a consistent and statistically significant direction of effect across two measures of cryptocurrency adoption. Remittances, investment and sins showed a consistent statistically significant effect across two models using the same measure of cryptocurrency adoption. For investment and sins, the direction of effect aligns with previous findings in the literature. The findings suggest a negative relationship between remittances and cryptocurrency adoption, contrary to what the existing literature suggests. The findings in relation to currency stability were inconclusive. CC were statistically insignificant across all models evaluated. The findings suggest additional factors not included in this paper influence the adoption of cryptocurrency, while also motivating more research into cryptocurrencies' use as an alternative currency. This paper contributes both to the cryptocurrency adoption literature and the currency substitution literature by integrating the fields in joint econometric models.

The remainder of this section focuses on defining and elaborating on the two most important concepts of this paper: cryptocurrencies and currency substitution. It then discusses the gap in the literature that this paper attempts to fill and the research question used to that effect. At the end of this section, a short roadmap is provided.

As mentioned, a definition of cryptocurrencies is required. The taxonomy of digital assets provided by Arslanian (2022) will be used. This paper defines cryptocurrencies as any digital asset falling into the bracket of being *fungible* and in the sub-bracket *payment token*. Fungibility refers to individual tokens being functionally equivalent; there is no reason to prefer one token of a certain digital asset over another. This is similar to how no distinction in the value of a fiat bill is made by the serial number alone. Within the fungible category, there are 3 categories, of which only the payment token is relevant for this paper. These are those fungible cryptocurrency assets designed to fulfill the functions of money (medium of exchange, store of value, unit of account). These tokens share the following general characteristics: time and location independent-availability, (theoretical) security, speed, low-fee transactions, irreversible transactions and (pseudo) anonymity. Three distinct sub-categories of these payment tokens are now discussed.

1.1 "Traditional" Cryptocurrencies

In contrast to fiat currencies, which derive their value from governmental decree and are backed by legal frameworks, traditional cryptocurrencies operate on a decentralized network of peer-to-peer transactions that do not rely on a central authority. This decentralized nature means that transactions are recorded on a distributed ledger known as blockchain rather than by a trusted intermediary like a bank. Some cryptocurrencies, most notably Bitcoin, have a function that reduces and eventually ceases the issuance of new coins through network design. This deflationary programming is different from fiat currencies, where the authorities usually target an inflation rate of around 2% annually (Ammous, 2018a; Central Bank News, 2025). The slow(ing) growth in supply of some cryptocurrencies, again notably Bitcoin, relative to the existing supply of coins is what leads to the idea that these cryptocurrencies are as stable in value as gold. This is because the stability in value of gold is attributable to the phenomenon of large existing stocks with slow growth in supply (Ammous, 2018b). Practically, Bitcoin's deflationary programming has worked so far, with average yearly price increases against major fiat currencies of around 100% since 2011, depending on which currency the price is measured against (Curvo, 2025). Other major cryptocurrencies like Ripple and Binance Coin use a similar system of a practically limited supply, even if the way the supply is limited is different from Bitcoin (Arslanian, 2022; Coin Market Cap, 2025). Despite the fact that demand also influences the price of cryptocurrencies, the lack of control by a single entity and slow growth have spawned the belief that cryptocurrencies are immune to inflationary pressures, government control, and political instability, which can all negatively affect those using fiat currencies.

1.2 Stablecoins

An important subset of payment tokens in relation to this research topic are stablecoins. These are cryptocurrencies that have prices linked to reference assets. They are different from traditional cryptocurrencies in that the price is driven by factors other than the initial programming and the collective actions of the users. Catalini et al. (2022) identify the main ways stability can be achieved:

1. Backing of the stablecoins by one or more fiat currency. This is the most common way stablecoins attempt to achieve price stability.

2. Backing of the stablecoin by one or more cryptocurrency, not issued by the same entity as the stablecoin.

3. Backing of the stablecoin by one or more cryptocurrency issued by the same entity as the stablecoin, which can be used to alter the price of the stablecoin, with the goal of maintaining a desired peg. This is also known as an *algorithmic* stablecoin.

4. A suggested market mechanism for stability has also been found in the research. Some papers argue that the increased demand for stablecoins during market downturns, rather than traditional cryptocurrencies, acts as an additional stabilizing force for stablecoins' prices beyond the currency architecture (Baur & Hoang, 2021; Lyons & Viswanath-Natraj, 2020).

Stablecoins have the potential to combine the stability benefits of well managed fiat currencies with the settlement speed and location independence advantages of payment tokens (Catalini et al., 2022). There is evidence that these tokens are already being used precisely for this. For example, a local Brazilian cryptocurrency expert spoke to Chainalysis on the large transaction volumes on Brazilian exchanges, stating "many of Brazil's exchanges and fintech brokerages offer USD[1]-pegged stablecoins to their customers...but at this stage, it appears that the main use cases for stablecoins are on the B2B[2] cross-border payments side" (Aaron Stanley as cited in Chainalysis, 2024, p. 33). While the consensus is that stablecoins are more stable than traditional cryptocurrencies, they have not managed to maintain the desired pegs to fiat currencies consistently (Baughman et al., 2022; Kosse et al., 2023). Despite these issues, the interest in stablecoins has increased from June 2023 - June 2024 (albeit less strongly compared to traditional cryptocurrencies) among institutions making transactions under USD 10M, with the share of stablecoin inflows on exchanges outside the United States increasing (Chainalysis, 2024). All of this is an indication that the stablecoin subset of cryptocurrencies will continue to be relevant in the future, particularly as a means of transaction.

1.3 Central Bank Digital Currencies

Central bank digital currencies are "a new form of digitized sovereign currency, generally conceived to be equal to physical cash or reserves held at the central bank" (Arslanian, 2022, p. 171). While the interest in such technologies is increasing, with most central banks (including every Group of 20 country's) exploring the issue, no major economy has created and fully launched one. At the time of writing, just the Bahamas, Jamaica and Nigeria have done so. Other countries have advanced pilot programs that already had transactions (Atlantic Council, 2025). Central bank digital currencies have many theoretical advantages as well as risks (Arslanian, 2022; Genc & Takagi, 2024). An extensive discussion of these is beyond the scope of this paper, particularly due to this application of cryptocurrency technology being in its infancy in terms of practical use and therefore of limited relevance to the data in this paper. The same governmental involvement in a digital asset that can bring substantial benefits also introduces a level of control by a small group of policymakers.

[1]USD: United States Dollar (abbreviation in original quote)
[2]B2B: Business-to-Business (abbreviation in original quote)

This control carries the risk of misuse, whether deliberate or unintentional, and potentially against the public interest.

1.4 Adoption of Cryptocurrencies

Cryptocurrency adoption has not been uniform. As Figure 1 shows, for those countries with available data, the number of survey respondents who said they use cryptocurrency was as low as 6% and as high as 47% in 2023. Factors driving cryptocurrency adoption vary across countries and are debated among researchers (see 2.2). Understanding the global drivers of cryptocurrency adoption, particularly in the context of factors that are more relevant for emerging markets with less developed financial systems, provides a valuable insight into cryptocurrency's potential future size and role in the global economy. This is especially important as recent years have seen substantial growth in the cryptocurrency interest coming from countries outside the high-income bracket (Chainalysis, 2024).

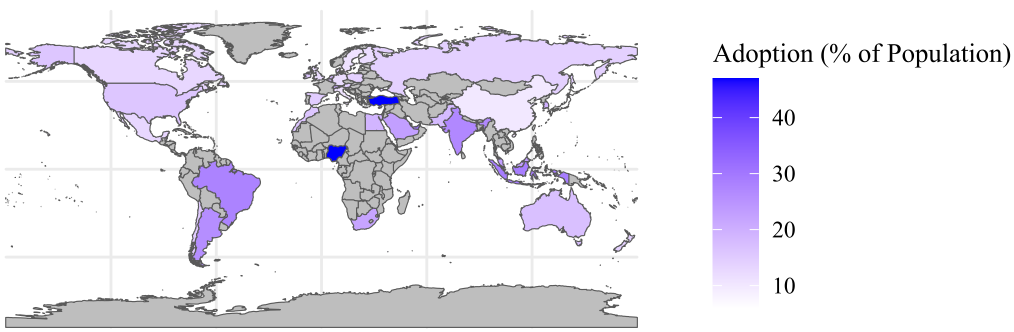

Figure 1: Map Showing Cryptocurrency Adoption Rates for 2023 (Statista, 2024b)

1.5 Decentralized Alternatives

Two key factors have led to the idea that cryptocurrencies can be used as an alternative to fiat currencies. These two factors are the **internet-based nature** and the **relative price stability** of cryptocurrencies, depending on the inflationary context. Firstly, the internet-based nature means that most people with a smartphone and internet can access the necessary infrastructure to buy, sell and own cryptocurrencies. This extends beyond political borders. There is nothing intrinsically hindering people or institutions in different jurisdictions from exchanging with each other. This is different to fiat currencies, where the ability of people to exchange currency with one another can be limited by the regulations applying to financial services companies and a lack of physical proximity, in the case of cash.

Secondly, depending on the context, the price of cryptocurrencies can be relatively stable, or at least volatile with a desirable upward trend in price, from the perspective of somebody owning the cryptocurrencies. Stability of local currency is usually measured either using inflation or the exchange rate to major currencies.

As mentioned earlier, evidence shows stablecoins may not match the stability of major currencies they normally track. However, stablecoins can be more stable than fiat currencies in economies experiencing higher levels of currency depreciation (Baughman et al., 2022; Kosse et al., 2023). As can be seen in Figure 2, the world's most popular stablecoin, by market capitalization, USD Tether has been stable against the USD.[3] The highest drop in monthly average value relative to the USD was less than 15% and this was an outlier in the coin's infancy. Particularly since January 2018, the monthly average price has experienced only small fluctuations (Coin Market Cap, 2025). The relative price stability of USD Tether becomes evident when looking at the depreciation of certain currencies against the USD. Table 1 shows the number of countries' currencies where the depreciation exceeded certain thresholds. 74 countries' currencies lost more than 25% of their value against the USD, while 29 lost more than 100% of their value against the USD in the time period 2014 - 2023. The true number of countries in these cases is likely higher, as some countries were unable to be evaluated due to lacking data. The point is that a stablecoin like USD Tether has the potential to outperform certain countries' fiat currencies when evaluating the metric of depreciation against a major currency like the USD. Meaning, there is a possibility for such stablecoins to act as a store of value.

When looking at traditional cryptocurrencies and their potential for acting as value storage, the evidence suggests something else. For simplicity, Bitcoin will be taken as the sole example here, as it is the largest by market capitalization (Coin Market Cap, 2025). Bitcoin has had an average yearly growth rate in value of around 100% since 2011, when measured against major currencies (Curvo, 2025). This far outpaces the global average inflation rate of 3.2% since 2011, and many countries' individual inflation rates (World Bank, 2024c). The volatility of the coin means investors need a long time horizon to reliably capitalize on these gains in value, and even then, due to cryptocurrencies only existing since 2008, there is limited long-term evidence for its value maintenance (Coin Market Cap, 2025). No specific research exists tracking the performance of multiple cryptocurrencies against multiple fiat currencies, either using inflation or depreciation. This is why some illustrative examples using the stablecoins and traditional cryptocurrencies with the most market capitalization are used here. The point illustrated is that both stablecoins and traditional cryptocurrencies have the potential to maintain, if not increase, their value when compared against various fiat currencies. They therefore could provide a viable alternative to fiat currencies from a store of value perspective.

Table 1: Number of Countries with Currency Depreciation Against the USD Exceeding Certain Percentages between 2014 and 2023 (World Bank, 2025)

Depreciation against USD (%)	Number of Countries
> 100	0
> 50	0
> 25	0

[3] In Figure 2 the y-axis shows only values above 500. This is done so changes can be visually assessed easier - visually this choice increases the deviations in value from the USD compared to using the full scale. The true scale begins at 0.

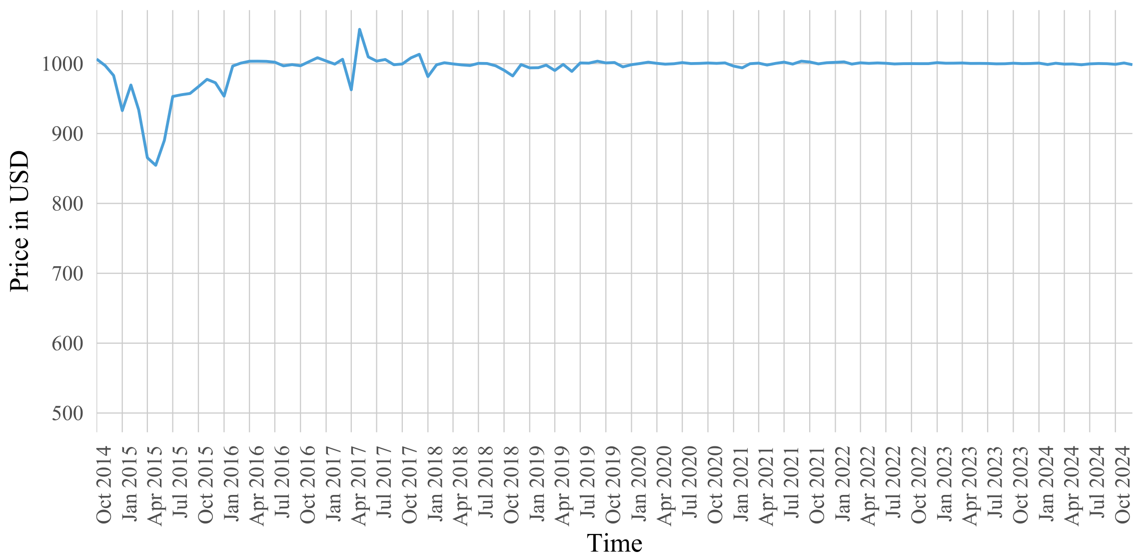

Figure 2: Value of 1000 USD Tether in USD (Statista, 2025b)

1.6 Currency Substitution

The use of alternative currencies by people is not new; there is an entire body of research devoted to understanding this practice, known as *currency substitution*. Currency substitution is defined by Calvo (2002) as the highly prevalent use of foreign fiat currencies to fulfill any of the three functions of money (store of value, means of exchange, unit of account). There is also something known as official currency substitution, which is when a government officially adopts a foreign currency as a legal tender in their own country. However, this paper refers to the personal and unofficial use by individuals. Inflation and unstable economic climates are key drivers when it comes to the use of foreign currencies (see 2.1 for a more detailed analysis). As such, the reasons that people may adopt foreign currencies are similar to the proposed benefits of cryptocurrencies. This leads to the idea that people could use cryptocurrencies rather than foreign currencies to fulfill their need of an alternative currency - this concept is known as *dollarization 2.0* (Peprah et al., 2018). Although the term contains the word of the USD, it does not imply that cryptocurrency replaces fiat currencies only in areas that have traditionally used the USD as an alternative. It implies the use of cryptocurrencies as an alternative to both domestic and foreign fiat currencies in countries that have traditionally used foreign currencies as an alternative to their own domestic fiat currency.

There are both theoretical and practical examples showing that the advancement of technology can facilitate the use of foreign currencies. Guidotti (1993) uses a theoretical model, arguing that a reduction in transaction costs spurred by financial innovation can promote foreign currency use as the cost of using foreign currencies is reduced by the new technology. A practical study of Nigeria by Ujunwa et al. (2021) find that markers of technology, such as internet banking transactions, are strong predictors of foreign currency use. It is therefore reasonable to argue that a new technology like cryptocurrency could promote the use of alternative currencies, even if it involves the use of a cryptocurrency rather than a foreign currency. This argument holds true as long as the use of the new technology and currency reduces the costs for those using said technology and currency.

This research paper draws upon the well-established theories of currency substitution to explore the factors driving cryptocurrency adoption. By examining the similarities between currency substitution and cryptocurrency adoption, this study aims to determine whether the predictors of currency substitution can be built into models of cryptocurrency adoption to improve the explanatory power.

1.7 Literature Gap and Relevance

The research is relevant for both academics and policymakers. The potential contribution to the academic literature is twofold. Firstly, existing models cannot fully explain the differences in adoption seen across countries. Secondly, and more innovatively, the paper provides an analysis (usually done on foreign currencies) for cryptocurrency through the lens of currency substitution. As will be seen in the subsection: Dependent Variable: Cryptocurrency Adoption, this research paper makes use of a new panel dataset of cryptocurrency adoption that will be able to capture the most recent trends in this area.

In terms of policymakers, it is important for them to understand how changes in underlying economic conditions may influence the use of cryptocurrency, as this will have policy implications. It is likely that questions around cryptocurrency will increase in importance in the future due to the increased interest and usage of cryptocurrencies globally, both from private individuals and governments looking to capitalize on the technology in various ways. Figure 3 shows the trend in cryptocurrency's market capitalization in USD from 2010 to 2025. This growth in market capitalization is evidence of increased interest in the technology among market players.

In addition to the increased market capitalization, policymakers have begun to carve out a space for blockchain technology in their economies in different ways. The most famous example is El Salvador legislating Bitcoin as a legal tender in their country in 2021 (BBC, 2021). However, there are other examples, like the canton of Zug in Switzerland allowing residents to pay taxes up to CHF (Swiss Franc) 1.5M with certain cryptocurrencies (Chainalysis, 2024; Kanton Zug, n.d.). Other countries have taken non-accommodative stances towards certain cryptocurrencies, including bans on use and transactions. The only major economy to outright ban a cryptocurrency is China. Regulations tend to focus only on Bitcoin rather than all cryptocurrencies, and no research exists tracking the exact nature of regulations (Nessi, 2025; New Hedge, n.d.). In summary, research aiming to understand drivers of cryptocurrency usage is likely to remain relevant or even increase in importance in the foreseeable future. This is particularly true for policymakers aiming to achieve regulatory or economic goals in relation to cryptocurrency.

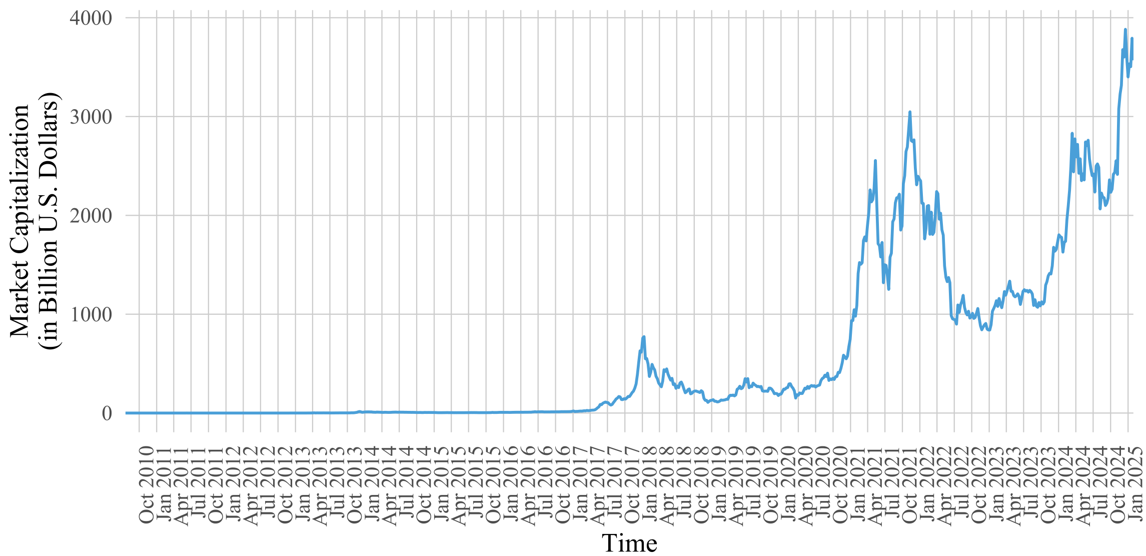

Figure 3: Cryptocurrency Market Capitalization 2010-2025 (Statista, 2025a)

1.8 Research Question

Due to the similarity in reasons for the adoption of foreign currencies and cryptocurrencies, this paper evaluates a model considering not only the predictors of cryptocurrency usage (currency stability, investment, wealth, sins, remittances, CC), but also the additional factor coming from the currency substitution literature (sovereign default risk) to see if including this can build an improved model of cryptocurrency adoption. These factors will be discussed in the next section, 2. Technology is not explicitly included as a predictor, despite its discovery in the literature. Technology is assumed to be fully covered by the introduction of cryptocurrency itself, a new technology.

The research question can be summarized as: *Do currency stability, investment, wealth, sins, remittances, CC and sovereign default risk affect the adoption of cryptocurrency?*

Roadmap

For the definition of the research topic, two questions/fields are of interest: "What drives currency substitution?" and "What drives the adoption of cryptocurrencies?" An overview of the research on the topics is provided in the literature review, separated into subsections on currency substitution and cryptocurrency adoption. From these reviews, the research question seen above was developed. Next, the methods, data and data transformation used to answer the research question will be discussed and visualized. Finally, the empirical results are shown, discussed and placed in the academic context to provide conclusions for researchers and policymakers interested in what factors can drive the adoption of cryptocurrency.

2 Literature Review

This section discusses the literature on both currency substitution and cryptocurrency adoption. The goal of this section is to understand which socioeconomic factors should be included in a study of cryptocurrency adoption aiming to consider, in addition, the theory on currency substitution. First, the currency substitution literature is discussed and then the cryptocurrency adoption literature.

2.1 Currency Substitution

There is a body of academic literature evaluating why individuals use foreign currencies, discussed in this subsection. Currency stability and the risk of sovereign default are identified as reasons that people may use foreign currencies. Those interested in a succinct visual overview of the currency substitution literature should visit Table 22 in Appendix 1.

2.1.1 Currency Stability

The stability of local currencies as a driver for foreign currency adoption is a debated issue in the academic literature. There are two main ways of looking at currency stability: inflation and exchange rate. These two ways of measuring currency stability are now discussed in the context of currency substitution.

Inflation Both perceived and real economic problems are identified in the literature as reasons for people to engage in currency substitution. The primary economic issue here is inflation. There are quantitative studies, such as those by Vieira et al. (2012) and Rennhack & Nozaki (2006), finding that inflation is a key predictor of currency substitution. Another quantitative paper Honig (2009) argues that lack of trust in the stability of the local currency leads people to use foreign currencies. Finally, an implicit argument for the viewpoint that inflation leads to currency substitution is made by Kokenyne et al. (2010) who argue that countries wishing to stop currency substitution from happening in their domestic economies should focus their efforts on taming excess inflation. This claim is backed up by a practical study of the Turkish economy by Taşseven et al. (2015) who argues that foreign currencies were used precisely due to the high inflation in the 1990s and then began falling out of favor as price stability increased. Levy (2021) makes a similar conclusion when he credits inflation first among a number of factors for the success of many Latin American countries to reduce currency substitution, oftentimes seen as negative by policymakers. Although a considerable number of studies credit inflation as positively related to currency substitution, one study focusing on Croatia, Slovenia and Slovakia by Stix (2011) did not find inflation to be a contributing factor to currency substitution.

Exchange Rate Another measure of currency stability - the volatility of the exchange rate to major currencies - is also oftentimes found to be important in relation to individuals using a foreign currency. Using a threshold autoregressive conditional heteroscedasticity (ARCH) model on 28 countries and an autoregressive distributed lag model of Nigeria, Ju (2020) and Ajibola et al. (2021), respectively, find that there is a correlation between the foreign exchange rate volatility and the use of foreign currencies. Contrary to these findings, the already mentioned study by Stix (2011) did not find exchange rate volatility to be a contributing factor to currency substitution.

2.1.2 Risk of Sovereign Default

The risk of sovereign default also appears in the literature on currency substitution, although less prominently than inflation. Vieira et al. (2012) find this to be a stronger predictor of currency substitution than inflation in their quantitative study on 79 economies at different levels of development. No other studies have evaluated this convincingly. Although Vieira et al. (2012) did cite a number of papers as foundations for evaluating the risk of sovereign default in their review, many of these do not clearly claim the logic applied by Vieira et al. (2012). Other studies in the area tend to focus on official currency substitution and the effect that this choice has on the risk of sovereign default (Berg & Borensztein, 2000; Sims, 2001). Limited consideration is given to the choice of individuals to use a foreign currency and how this choice is influenced by the risk of sovereign default. However, the study by Vieira et al. (2012) clearly shows its importance, and therefore this factor should be included in any comprehensive study examining the underlying factors behind currency substitution and their role in driving cryptocurrency adoption.

2.2 Adoption of Cryptocurrency

In parallel to the currency substitution literature, there is a wide body of literature studying the usage of cryptocurrency. The literature finds inflation, investment, wealth, sins, remittances and CC as factors connected to the adoption of cryptocurrency. Many of these studies focus on Bitcoin specifically rather than cryptocurrencies as a whole. However, since Bitcoin is the largest cryptocurrency by market capitalization, Bitcoin can serve as an analytic proxy for cryptocurrency as a whole (Coin Market Cap, 2025). Readers interested in a succinct visual overview should visit Table 23 in Appendix 1.

2.2.1 Currency Stability

There are a number of studies that have evaluated the relationship between cryptocurrency and currency stability, usually measured through inflation. Choi & Shin (2022), Conlon et al. (2021) and Gaies et al. (2024) study time series data on Bitcoin prices and find that they are correlated positively to inflation or inflation expectations. Mixed evidence is presented by Phochanachan et al. (2022), who find the inflation hedge is only present in the short term. Chainalysis (2024) evaluated Argentine stablecoin trading data on the leading local exchange Bitso and found that with each devaluation against the USD (associated with an increase in Argentine inflation), the monthly stablecoin trading volume on Bitso increased. This indicates trading volume increases in response to the Argentine peso losing value and associated inflation. Similar results but evaluated for Bitcoin instead of stablecoins exist in Venezuela (Chainalysis, 2024). Academic case studies of countries using cryptocurrency in response to inflation are limited; only Taskinsoy (2019) comes up. He argues that the relative instability of the Turkish Lira is what drives many in the country to use Bitcoin instead of the local currency.

Studies similar in methodology to those mentioned in the paragraph above study time series data of inflation and the price of Bitcoin; these, however, find no significant correlations (Basher & Sadorsky, 2022; Smales, 2024). In studying country economies using cross-sectional data, both Parino et al. (2018) and Ricci (2020) find that there is a negative correlation between inflation and the price of the cryptocurrency Bitcoin. However, it should be noted that the former focused on data from before 2015, which may have been too early to see adoption in developing countries. The latter only evaluated already developed economies, which have seen lower levels of inflation compared to developing countries.

2.2.2 Investment

Investment is found as a key use case for the purchase of cryptocurrencies. Voskobojnikov et al. (2020) conducted interviews among North American respondents and found that investment is one of the main intended uses of cryptocurrency among non-users. Quantitative studies support this idea. Glaser et al. (2014) find that the pattern of trading on the now-defunct Mt. Gox cryptocurrency trading platform imply that users were investing, not using the currency for payments. The authors argued that while the value of currencies on individual accounts did change, the total value on the exchange did not change significantly. To the authors, this suggested that users were shuffling funds between each other but not using the cryptocurrencies for payments. In the case of payments, funds would have had to leave the exchange because it is unlikely the sellers of most goods and services would have been on the exchange. Therefore, in a payment use case, the overall value of coins on the exchange would have had to change, but this did not happen.

2.2.3 Wealth

Wealth is a well-established factor connected to cryptocurrency in academia, studied through various methods. Lammer et al. (2019) studied German bank accounts and found wealthier people were more likely to own Bitcoin. This conclusion is supported, on a national scale, by Parino et al. (2018) who found Gross Domestic Product (GDP) per capita to be positively correlated to Bitcoin ownership. Further survey-based evidence on the average cryptocurrency user is provided by Gemini (2021) who find the average American cryptocurrency investor has a household income of USD 110K, more than 1.5 times the national average for that year. It should be noted that the survey was not representative and explicitly only included those with a household income above USD 40K, meaning the real average household income of the average investor is likely lower. While these sources do not aim to understand the reasons to why wealthier people are more likely to own cryptocurrencies, a possibility is that generally volatile cryptocurrencies may only be bought by those who can afford to take temporary losses when the price of the asset decreases.

2.2.4 Sins

The use of cryptocurrencies in areas that are illegal or immoral is also a driver of their usage in many cases. Due to the diversity of illicit use cases, only some illustrative examples will be presented here. They range from using Bitcoin to pay for illicit goods and services, such as was possible on the now-defunct Silk Road dark-web sites (Saurabh, 2017). Research has also found that in countries with larger shadow economies, the Bitcoin trading volume is more strongly responsive to shocks to the shadow market (e.g., raids and seizures by law enforcement), indicating the cryptocurrency Bitcoin is used for illicit transactions (Marmora, 2021).

Cryptocurrencies may also be used by sanctioned countries to settle international debts. Iranian academics have evaluated the possibility of using cryptocurrencies to settle debts for their resource exports, which is difficult to do in the current international settlement architecture given the international sanctions placed on the country (Sarvi, 2020). Venezuela developed the *Petro*, a cryptocurrency with value tied to the country's oil reserves. It was meant to serve as a means of settling international payments for the sanctioned country. The project was discontinued in 2024 (Macfarlane, 2021; RFI, 2024).

Sanctions on individuals also appear to drive the adoption of cryptocurrencies. According to an analysis by Chainalysis (2020) 75% of all cryptocurrency transactions on a randomly selected Venezuelan exchange were over USD 1K. Given the low wages in the country, it is likely that this represents sanctioned individuals who have profited from the regime, attempting to move funds out of the country. Similarly, Russian language cryptocurrency exchanges without Know Your Customer (KYC) regulations have tripled since the start of the war in Ukraine and the following sanctions on both individuals connected to the Kremlin and ordinary Russians. The idea that this growth is connected to the sanctions is supported by the absence of growth in Russian-speaking exchanges that do conduct KYC checks and presumably comply with international sanctions (Chainalysis, 2024). Further evidence is provided by Alnasaa et al. (2022), who see higher adoption of Bitcoin in more corrupt countries, which will have more individuals sanctioned by the international community.

2.2.5 Remittances

Another potential reason for the adoption of cryptocurrency is for remittance payments. This has not been studied extensively academically, but the economic fundamentals and some practical examples show the potential. Fees for remittance payments can be very expensive, between 6.9 - 20% according to Ruehmann et al. (2020). Simultaneously, blockchain technology can have incredibly low fees, typically between 0 - 1% according to Dyhrberg et al. (2018). This low cost has led some academics like Folkinshteyn et al. (2015) to argue cryptocurrencies like Bitcoin could form an important aspect of lowering remittance costs. This cost advantage was the official reason behind El Salvador making Bitcoin legal tender in 2021 (BBC, 2021). Data from other areas and cryptocurrencies supports the cost idea as well. Chainalysis (2024)'s data suggests 60% lower costs for a USD 200 payment from sub-Saharan Africa when using a transfer system based on stablecoins compared to a traditional fiat-based system. In addition, there was at one point a concerted effort by the Libra Association (led by Meta) to release a stablecoin that was to be integrated with existing and widely used communications platforms such as WhatsApp. Through this integration, it had the potential to provide basic banking services to the 1.1 billion people globally who have a mobile phone but no bank account (World Bank, 2018). While challenges like internet access and user identity verification would have remained, the potential of this stablecoin integrated in existing communication services for remittances was hard to deny (Ruchti, 2019). Ultimately, the project ended due to regulatory opposition from the United States (McNickel, 2024). All of that is to say that the potential for cryptocurrencies or the blockchain architecture to increase financial inclusion is not only supported by economic fundamentals but has been explored by reputable market players. It is therefore worth including a proxy for remittances in an analysis on cryptocurrency adoption.

2.2.6 Capital Controls

There exists research that claims CC are relevant to the adoption of cryptocurrency. Carlson (2016) conducts expert interviews on Argentina and finds that CC can and are being circumvented using Bitcoin. Hu et al. (2021) studied Chinese Bitcoin transactions and concluded that 25% of the transaction volume represents capital flight out of the country. Viglione (2015) finds a similar result in a quantitative analysis of multiple economies. They see a premium being paid for Bitcoin in these countries, which they interpret as “extra demand” (Viglione, 2015, p. 6). Additional evidence for the importance of CC is provided by Alnasaa et al. (2022), who ran a cross-country analysis including CC as a predictor and found the CC to be a statistically significant predictor of cryptocurrency usage. The study of CC as a predictor in any field is limited by the diversity of potential measures to restrict capital flow and the lack of a standardized metric.[4]

[4]Note: An index such as the one produced in this paper from regularly published International Monetary Fund (IMF) data could form the basis for a consistent and replicable study of CC. See subsection 4.2.

3 Methodology

This section discusses the quantitative methods to answer the research question. It is organized as follows: firstly, common terms among the models are introduced, then the formulas defining the fitted input-output relationship between the independent and dependent variables are described, with additional terms being defined where necessary. Next, the hypothesis and significance level are discussed. Finally, benefits and drawbacks are discussed in relation to how well the methodology can answer the research question. Please note that in addition to these 3 models, an additional robustness check using a different dependent variable is performed. However, for this the description is done separately in 5.2.4 as it is addressed in less detail.

3.1 Common Terms

The models have a number of common terms. These are listed and explained below:

$\beta_{1,2...7}$: Coefficients for each independent variable. The exact interpretation of these depends on the input-output relationship specified in the models. They all describe a certain change in the dependent variable connected to a change in the respective input variable.

i: Denotes the cross-sectional unit (country) in the panel data.

t: Denotes the time unit (year) in the panel data.

ε: The error term, capturing unobserved factors.

3.2 Model 1: Linear Regression - No Transformation

The first model is a linear regression with the temporal aspect modeled as a categorical variable. A statistically significant term for the year dummy will have no effect on answering the research question. The formula can be seen below. The results for this model can be seen in 5.2.1.

$$
\begin{aligned}
\text{Cryptocurrency Adoption}_{i,t} = \beta_0 + \sum_{t=2020}^{2023} \beta_t \cdot D_t \\
&+ (\beta_1 \cdot \text{Currency Stability}_{i,t}) \\
&+ (\beta_2 \cdot \text{Investment}_{i,t}) \\
&+ (\beta_3 \cdot \text{Wealth}_{i,t}) \\
&+ (\beta_4 \cdot \text{Sins}_{i,t}) \\
&+ (\beta_5 \cdot \text{Remittances}_{i,t}) \\
&+ (\beta_6 \cdot \text{CC}_{i,t}) \\
&+ (\beta_7 \cdot \text{Sovereign Default Risk}_{i,t}) + \varepsilon_{i,t}
\end{aligned}
$$

The group of terms $\sum_{t=2020}^{2023} \beta_t \cdot D_t$ represent the categorical variables of each year, with the first year as the baseline. The dummy D_t is 1 when the corresponding year is "present" and 0 otherwise. It ensures that for each year only the relevant shift in response variable is performed, as only the one relevant year's term will be counted towards the summation. The summation starts at the year 2020, instead of the first year, 2019, in the dataset, because 2019 is the baseline. β_t specifically is the linear offset in dependent variable for the specific years.

β_0: The intercept, representing the baseline level of cryptocurrency adoption when all continuous predictors are equal to zero and the year is at the 2019 baseline (Utts & Heckard, 2012; Vaart, 2019).

The terms $\beta_{1,2\ldots7}$ represent the response in dependent variable as a result of increasing the corresponding variable by 1 while holding all of the other variables constant (Utts & Heckard, 2012; Zicha, 2020).

Untransformed linear regressions are seen as a suitable initial model to test relationships between variables, offering strong interpretability when the underlying relationship is assumed to be linear. In the absence of evidence to the contrary, this model is therefore used.

3.3 Model 2: Linear Regression - Transformation

The second model extends the previous model by explicitly transforming variables. All dependent variables except for the categorical years are transformed. This is done to better meet the assumptions of a linear regression, which requires normally distributed variables and residuals. As will be seen in the subsection 5.1, not all variables clearly meet this assumption. It is therefore suitable to run a model with transformations applied. The interpretation of the coefficients will become different as a result of the transformations. The Yeo-Johnson transformation will be used. This is an extension of the Box-Cox transformation, allowing both negative and zero values, which are present in the data studied (Weisberg, 2001). The results of this model can be seen in 5.2.2. The Yeo-Johnson transformation makes the following transformation by estimating a λ value from the data (Weisberg, 2001). The exact values for λ used for the variables can be seen in Table 7 in section 4.3.

$$\psi(X,\lambda) = \begin{cases} \frac{(X+1)^{\lambda}-1}{\lambda} & \text{if } \lambda \neq 0, X \geq 0 \\ \log(X+1) & \text{if } \lambda = 0, X \geq 0 \\ \frac{-\left[(-X+1)^{2-\lambda}-1\right]}{2-\lambda} & \text{if } \lambda \neq 2, X < 0 \\ -\log(-X+1) & \text{if } \lambda = 2, X < 0 \end{cases}$$

This means that the formula for the transformed linear regression becomes the following:

$$\begin{aligned} \text{Cryptocurrency Adoption}_{i,t} = \beta_0 + &\sum_{t=2020}^{2023} \beta_t \cdot D_t \\ &+ \beta_1 \cdot \psi(\text{Currency Stability}_{i,t}, \lambda) \\ &+ \beta_2 \cdot \psi(\text{Investment}_{i,t}, \lambda) \\ &+ \beta_3 \cdot \psi(\text{Wealth}_{i,t}, \lambda) \\ &+ \beta_4 \cdot \psi(\text{Sins}_{i,t}, \lambda) \\ &+ \beta_5 \cdot \psi(\text{Remittances}_{i,t}, \lambda) \\ &+ \beta_6 \cdot \psi(\text{CC}_{i,t}, \lambda) \\ &+ \beta_7 \cdot \psi(\text{Sovereign Default Risk}_{i,t}, \lambda) + \varepsilon_{i,t} \end{aligned}$$

The group of terms $\sum_{t=2020}^{2023} \beta_t \cdot D_t$ has the same interpretation as in Model 1.

3.4 Model 3: Fixed Effects

Panel data gives the choice between fixed or random effects to account for omitted variable bias. In practical applications, the choice between fixed or random effect is decided using the Hausman Test (Dougherty, 2011). The results of this test can be seen in Table 9 in 5.1.3. The Hausman Test indicates that a fixed effects model should be used.

Fixed effects control for time invariant-differences, unobserved differences between countries. It allows accounting for unobserved factors (like culture or policies) that do not change over time and therefore isolating the changes in the dependent variable associated with changes in the independent variable (Torres-Reyna, 2007). Explicitly including the year as a predictor is not done as it is unlikely that the time effects influenced the cryptocurrency adoption in countries in the same way. This is mainly due to the different policy responses to Covid-19 and associated socioeconomic consequences, which were vastly different globally. The formula for the fixed effects model can be seen below. The results of Model 3 can be seen in 5.2.3.

$$\begin{aligned} Adoption_{it} = \beta_1 \cdot \text{Currency Stability}_{it} + \beta_2 \cdot Investment_{it} + \beta_3 \cdot Wealth_{it} + \beta_4 \cdot Sins_{it} \\ + \beta_5 \cdot Remittances_{it} + \beta_6 \cdot \text{CC}_{it} + \beta_7 \cdot \text{Sovereign Default Risk}_{it} + \alpha_i + \varepsilon_{it} \end{aligned}$$

The term $\varepsilon_{i,t}$ represents the error term for each country and time.

The term α_i represents country specific, time invariant effects. It can be understood as the effect of being country i on the response variable. It is a linear offset in response variable which does not vary with time or any input variable (Dougherty, 2011).

Notice the loss of the intercept β_0. The global intercept is replaced by country specific intercepts (Dougherty, 2011).

3.5 Hypothesis

Formally, the null and alternative hypothesis, for all models, in words and mathematically, are seen below:

Null Hypothesis

H_0: Currency stability, investment, wealth, sins, remittances, CC and sovereign default risk have no statistically significant effect on cryptocurrency adoption.

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$$

Alternative Hypothesis

H_1: At least one independent variable has a statistically significant effect on cryptocurrency adoption.

$$H_1 : \exists \beta_j \neq 0, \quad \text{for at least one } j \in \{1, 2, 3, 4, 5, 6, 7\}$$

Direction of Effect

The alternative hypothesis does not specify a direction of effect due to the exploratory nature of this paper, which is testing the integration of a proxy. Furthermore, much of the research into cryptocurrency adoption is conflicting. This makes not using a specific direction of effect in the alternative hypothesis an appropriate choice.

Significance Level

Due to the limited data size and therefore reduced statistical power of this paper (see Underlying Data) a significance level at the upper end of the normal range ($\alpha = 0.1$) will be used.

3.6 Generalizability

Due to the broad range of countries included in this study, the generalizability of the results should be sufficient to account for most countries in the world. Figure 4 shows the countries available in the Statista (2024b) dataset and being studied explicitly in this paper. It is clear that a diversity of countries are represented by the data, in different socioeconomic aspects, such as those found to be relevant in the literature review for both currency substitution and cryptocurrency adoption. The main criticism in terms of generalizability is the under-inclusion of African countries, with just 4 out of the 54 countries on the continent represented. Nevertheless, the argument can be made that this research will be applicable to most countries whose economic data falls within the range of the independent variables. Extreme political and economic outliers (e.g., North

Korea) will not fall within this scope, but that is typical of almost any national level panel data analysis.

In the case of fixed effects models (Model 3 and Model 4, the latter introduced later), generalizability is limited by the model design since coefficients a_i in the model are calculated only for countries in the sample. Model 1 and Model 2 do not explicitly model the country as an input variable used to make predictions on unseen countries, meaning their generalizability is superior relative to Model 3 and Model 4.

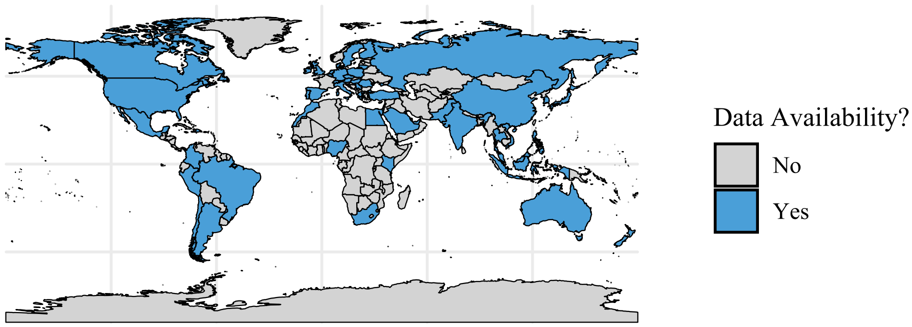

Figure 4: Map Showing Countries With Available Cryptocurrency Adoption Data (Statista, 2024b)

4 Underlying Data

This section discusses the underlying data used for this research paper. For some of the data presented here, the country variable is already altered before the presentation in this paper using the library {countrycode}, which can take different versions of country names and obtain the relevant three-letter code. For those cases, it means that in the data source there was a country name rather than a country code. All data, as well as the .Rmd file associated with this paper can be found by visiting the GitHub page linked in Appendix 4. The section proceeds by first discussing the dependent variable data, followed by the data used as proxies for the independent variables.

4.1 Dependent Variable: Cryptocurrency Adoption

Cryptocurrency adoption is measured using a 2024 dataset by Statista (2024b). The dataset is the result of multiple surveys where respondents were asked if they had used cryptocurrency in a given year. The data's first five rows can be seen in Table 2. Due to the unavailability of data for the other variables for the year 2024, only data up to 2023 will be used in the statistical analysis. The data is available for 56 countries of different levels of economic development.

The data quality is sufficient given practical constraints. While the survey was not representative of the respective country's population and voluntary, opening the data quality up to self-selection issues, the only feasible improvement could have been a mandatory national census, conducted across countries. However, the effort in standardizing questions and timings across countries is prohibitive in practice. The authors describe their approach to data collection. It is clear and professional: sample sizes of at least 2K people per country, checks for bots, checks for speed racers and the survey was performed in the official languages of the country (Statista, 2020). Overall, the quality of this variable is sufficient for the purposes of this research.

Table 2: Percentage of Respondents Reporting Cryptocurrency Use in 2019-2024 (Statista, 2024b)

Country	2019	2020	2021	2022	2023	2024
ARG	16	14	21	35	26	30
AUS	7	8	9	16	17	16
AUT	8	7	8	14	14	14
BEL	7	6	10	15	16	15
BRA	18	12	12	22	28	24

4.2 Predictors: Independent Variables

Table 3 shows an overview of the indicators used as proxies for concepts discovered in the literature review and their sources. The indicators for wealth, remittances and risk of sovereign default are self-explanatory and of sufficient quality. Those indicators are sourced primarily from the World Bank, a standard data source for country-level economic data. In the case of missing individual data points, additional sources were used to augment the data where possible. The details of those manual imputations are discussed in 4.3.

Table 3: Overview of Data Sources for Independent Variables

Indicator	Proxy for	Primary Source
Inflation, consumer prices (annual % change)	Currency Stability	World Bank (2024c)
Gross domestic savings (GDS) (% of GDP)	Investment	World Bank (2024b)
GDP per capita (current USD)	Wealth	World Bank (2024a)
Personal remittances received (RR) (% of GDP)	Remittances	World Bank (2024d)
External Debt (ED) (% of GDP)	Risk of Sovereign Default	Focus Economics (2024)
Political Corruption Index	Sins	V-Dem (2024)
Bespoke CC Index	CC	IMF (2024)

The data used as proxies for currency stability, investment, sins and CC must be discussed and justified in further detail as they are not self-explanatory.

Currency Stability

The literature review showed currency stability, through exchange rate and inflation, to be an important determinant of both currency substitution and cryptocurrency adoption. This paper will use only the inflation rate as a proxy for currency stability as a whole. This choice is made for three reasons. Firstly, inflation and exchange rate are related and move together under normal circumstances, as shown in several research articles (Asari et al., 2011; Fetai et al., 2016; Sek et al., 2012). This means the inflation rate can be used as an effective proxy for the exchange rate. Secondly, since they move together, there could be the issue of multicollinearity if both of them were included (Statistics Solutions, n.d.). Thirdly, as already mentioned, due to the limited data quantity, the inclusion of more predictors would have an adverse effect on statistical power, which is not a justifiable trade-off given the two previously mentioned points.

Investment

Investment is closely related to savings in national accounting, although the strength of this relationship varies across economic models. In the classical model of a closed economy without government spending, savings are equal to planned investment (Mitchell et al., 2019). This makes GDS as a percentage of GDP a reasonable proxy for the funds available for investment. This indicator is used as a proxy for the investment use case of cryptocurrency discovered in the literature review.

Sins

A single indicator is used to encompass all the sinful uses of cryptocurrencies identified in 2.2.4. The two primary sinful uses are criminality and the circumvention of sanctions. Since the international community routinely sanctions individuals and not the countries themselves based on corruption, human rights abuses and other serious accusations, it makes sense to use corruption as a proxy for individual sanctions that people may attempt to circumvent using cryptocurrency (U. S. Department of the Treasury, 2022). Using corruption as a proxy for crime is also a possible approach, as the link between corruption and (in particular organized) crime has been shown across several regions and studies (Buscaglia & Dijk, 2003; Democracy, 2010; Mazzitelli, 2007).

The political corruption index, published by V-Dem (2024), is used in an attempt to cover both crime and corruption. The index is made up of several subsets of corruption. In a study with more data quantity available, it would be appropriate to use specific types of corruption from this index combined with other indicators for criminality (e.g., murder rate). However, due to the already limited data size, the trade-off of including several variables for the sin attributes identified in the literature would be too adverse on the statistical power. Therefore, the aggregated corruption index is used rather than a specific corruption indicator combined with a separate criminality proxy (Olin, n.d.). The V-Dem (2024) data can be downloaded directly via library {vdemdata} in R-Studio after connecting to GitHub. The data is available only up to and including 2023. This index ranges between 0 (lowest possible corruption) and 1 (highest possible corruption).

Capital Controls

Since CC have been identified as important in literature review on cryptocurrency adoption, they must be accounted for in a model attempting to explain cryptocurrency adoption; a bespoke index is created to do that. There is a lack of structured and recent data around CC. Outdated structured data does exist (Fernandez et al., 2016). The source used here will be from the online query tool of IMF (2024) which allows the recovering of information contained in the annually published Report on Exchange Arrangements and Exchange Restrictions, specifically the five indicators: controls on personal payments, prior approval, quantitative limits, indicative limits / bona fide test and controls on personal capital transactions. The key limitation of this dataset is that the data is only available up to and including 2022. Techniques to deal with missing data will be used to make this dataset usable. The first five rows of the raw data can be seen in Table 4.

Table 4: Head of IMF (2024) CC Dummy Data

Year	IFS Code	Country	Controls on Personal Payments	Prior Approval	Quantitative Limits	Indicative Limits / Bona Fide Test	Controls on Personal Capital Transactions
2019	512	Afghanistan	no	no	no	no	no
2019	914	Albania	no	no	no	no	no
2019	612	Algeria	yes	yes	no	yes	yes
2019	614	Angola	yes	no	yes	no	yes
2019	311	Antigua and Barbuda	yes	yes	yes	yes	NA

Table 5: Head of Table with Bespoke CC Index

Country	2019	2020	2021	2022	2023
AFG	0.0	0.0	0.0	0.0	NA
ALB	0.0	0.0	0.0	0.0	NA
DZA	0.8	0.8	0.8	0.8	NA
AGO	0.6	0.6	0.6	0.6	NA
ARG	1.0	1.0	1.0	1.0	NA

In order to create a quantitative variable encompassing all CC as a whole, these variables will be turned into a bespoke index from 0 (least capital controls) to 1 (most capital controls) by assigning a value of 1 for each “Yes” and 0 for each “No” and then dividing the result by the number of available data points for that country in that year. Conceptually, this means that an index score calculated with just one available data point looks identical to one with all data points available. By using an equally weighted index-generating method, the assumption is made that each of these types of restrictions is equally important in the types of CC that influence the adoption of cryptocurrency. In the case that a country has no data point (only the case once in the data), a NA is assigned to this value. Table 5 shows the top five rows of the resulting data frame containing the index.

4.3 Data Preparation

This subsection discusses how the data is treated to prepare it for analysis. The procedures are outlined below. A list of country codes was used at various points throughout the analysis to combine datasets, sourced from Institute for Research on Worlds Systems (n.d.).

Removing Countries without Cryptocurrency Adoption Data

Countries without a dependent variable are removed in this step. Without a dependent variable limited, insight can be gained, even if all the dependent variables are available. Due to lacking independent variable data, the value for Taiwan is also removed. If the number of countries in the dataset (56) approached the number of countries in the world (193), imputation methods to deal with missing variables could be used for the dependent variable. However, given the low proportion of available countries, this is not feasible in this particular case.

Removing Year 2024 from Cryptocurrency Adoption Data

Since there is no data for any of the other indicators for the year 2024 in a structured and accessible format, the year 2024 is removed from the data on cryptocurrency adoption.

Manually Adding Missing Data

Due to the already limited data size, where possible, missing independent variables are filled in manually. While this approach limits practical replicability, it offers the benefit of retaining slightly increased data quantity, which is a worthwhile tradeoff given the already low data quantity. The following information was added in this manner:

- Argentina inflation rate 2018-2022 (Statista, 2024a)
- Nigeria GDS (% of GDP) 2018-2021 (Trading Economics, 2024)
- Belgium, Canada, France, Ireland, Spain ED (% of GDP) 2018-2023 (CEIC Data, 2025)

Missing Data Structure

Since not all data can be added manually due to lacking reliable and consistent data sources, alternative techniques must be employed to deal with missing data. The way that missing values are dealt with depends on the quantity and structure of missing data. A standard approach is to say that any dataset having less than 5% missing data can be treated with univariate imputation, such as adding the mean of a row or column for a missing piece of data. However, when more than 5% of the data is missing, the structure of the missing data begins to be more important, and univariate imputation may no longer be appropriate. A Missing Completely at Random (MCAR) test can be used to check if univariate imputation is suitable for data with more than 5% missing (Schwarz, 2024). The results of the MCAR test can be seen in Table 6. The results indicate that univariate imputation can be used for all variables because the hypothesis that the data is not MCAR is either rejected at the 5% level or the number of missing values is less than 5%. The percentage missing column in the table applies only to the numeric columns, so the inclusion of country names in the data frame does not downward skew the proportion of missing numbers.

Table 6: MCAR Test Results

Dataset	Test Statistic	Degrees of Freedom	P-Value	Nr. Missing Patterns	Proportion Missing (%)	Significance Level
Adoption	16.75	17	0.4713	5	9.45	Not significant
Inflation	6.39	9	0.6998	3	1.09	Not significant
GDS	34.5	12	6e-04	4	3.64	Highly Significant
GDP	-	- No	Missing	Values	0.00	-
RR	2.95	1	0.0861	2	1.82	Not significant
ED	-	- No	Missing	Values	0.00	-
Corruption	-	- No	Missing	Values	0.00	-

The MCAR test could not be performed for the CC data as there is an entire column missing, as can be seen in Figure 5. Such a structure is incompatible with the algorithm of the MCAR test. Therefore, in the interest of maintaining the highest reasonable data quantity, the 2022 (most recent) value will be imputed as the 2023 value. The logic behind this imputation is twofold. Firstly, it is unlikely for CC to significantly change in a single year, as it would require a policy shift. Secondly, this type of imputation should be applied here, since mostly complete data is available for the other indicators for 2023. Removing another year for the whole analysis would further compound the data quantity issue. For a detailed guide on the interpretation of the Missing Data Pattern figure, please see subsection 4.3.

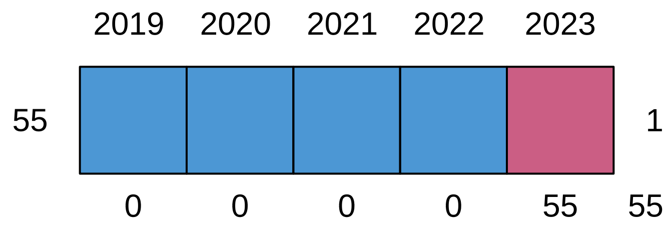

Figure 5: Missing Pattern of Bespoke CC Index based on IMF (2024)

Imputing Missing Data

Since the missing data for all variables, except CC, is of a structure that can use univariate imputation, as shown by the MCAR tests, this is done. The assumption behind the way that the imputations are done is that the country in which an observation happens is more important than the year in which it happens. Thus, it is preferred to impute using the country's available data for an indicator over the year's available data for an indicator. Due to this dataset taking place during the Covid-19 pandemic, it would not be suitable to just take a mean of all available years for a country. Instead, the average of the year before and after the missing data is used. If a data point is missing in the last year, only the previous available year's data from that country is used. If a data point is missing in the first year, only the first available year's data point of that country is used to impute. As can be seen in Figures 23 through 28 in Appendix 2, there are cases where the missing pattern is not in between available data points and the algorithm will rely on a single number for imputation. For the sake of brevity, this process is referred to as Nearest Average Imputation (NAI).

To be exact, the following imputations are performed:

- Adoption, inflation, GDS data completed using NAI.
- No imputation required for GDP, corruption and ED data (complete data).
- Average for all observations, separated by year, imputed for one country in the remittances data, as there were no values for any year for that country (United Arab Emirates). No further imputations had to be applied.
- No imputations are required for the CC data beyond the year 2023, which was imputed using the 2022 data as previously mentioned.

With those changes, the data is ready for analysis. Note that all datasets are run through the algorithm to perform the NAI to increase practical replicability of the underlying script.

Interpretation of Missing Data Pattern Figure

This guide is relevant for Figures 5 and Figures 23 through 28. The figures consist of horizontal bars, one for each of the configurations of missing data. Blue represents a present year and red an absent year. The top headings represent the row headings. The number to the left of each bar represents the number of times a configuration of missing data is represented in the dataset. The number on the right represents the number of missing data points in a single observation for a particular configuration of missing data. The numbers in the footer represent the number of times a particular feature is missing across the dataset. The number at the bottom right represents the total number of missing variables for each dataset.

Yeo-Johnson Transformation

The Yeo-Johnson transformation was applied using the package {caret}. First, a function is used to estimate the lambda parameters of transformable predictor variables. Table 7 shows these estimates. It should be noted that the Country Name variable was not transformed because it is not numeric. The variable for the years will be treated as categorical and is therefore also not transformed. The data on CC initially exhibited insufficient variability to permit the Yeo-Johnson transformation. To address this, small perturbations were introduced, drawn from a distribution with a mean equal to 0 and a standard deviation equal to 6% of the range of the original CC variable. This was the smallest level of adjustment that enabled a successful transformation.

Table 7: Yeo-Johnson Transformations Lambda Estimates

Variable	Lambda Estimate
Inflation	0.1596
GDS	0.4302
GDP	0.2493
Corruption	-1.6004
RR	-0.9531
CC	-2.9172
ED	-0.1598

5 Empirical Findings

This section discusses the empirical findings. It first looks at descriptive statistics of the data, including histograms and a correlation matrix. This is done to assess if the data fits model assumptions. As part of the descriptive statistics, a Hausman test is done to determine the choice between a fixed and random effects panel data model. Next, the results of the models are discussed, primarily in terms of the predictor variable's coefficient estimates and model quality. The fixed effects model is determined to be the best. Finally, a robustness check using a different proxy for the adoption of cryptocurrency is conducted in an additional fixed effects model (Model 4).

5.1 Descriptive Statistics

This subsection shows the exploratory analysis of the data to prepare for inferential statistics by checking if assumptions for certain models are met. The entire description of data from here on out is performed on the imputed data. In the case of the CC data that was Yeo-Johnson transformed, the data seen from here on out reflects the values including the perturbations added to enable the transformation. Summary statistics of the data used in Models 1, 2 and 3 can be found in Table 24 in Appendix 3.

5.1.1 Distribution of Variables

Histograms are a common way to visually assess the distribution of a list of values. In applied settings, a distribution that approaches a normal one is an underlying assumption of many models, and therefore it is crucial to assess this. Histograms plot the frequency (y-axis) at which values occur between certain ranges (x-axis). In a distribution approaching a normal one, there is a single range in which the most values occur, and then the frequency of values in ranges reduces the further away the ranges move away from the most populated range, in both the positive and negative direction.

Figure 6 shows the distribution of the cryptocurrency adoption data in both transformations. Please note that since the Yeo-Johnson transformation was applied only to the independent variables, both distributions are identical. Both histograms are shown for completeness only. The distribution of adoption values is right-skewed, with the majority of observations concentrated between 5 and 20. A sharp peak occurs around 10 to 12, followed by a gradual decline and a long tail extending toward higher values. The Shapiro-Wilk Test confirms a significant deviation from normality ($p < 0.001$), indicating a non-normal distribution.

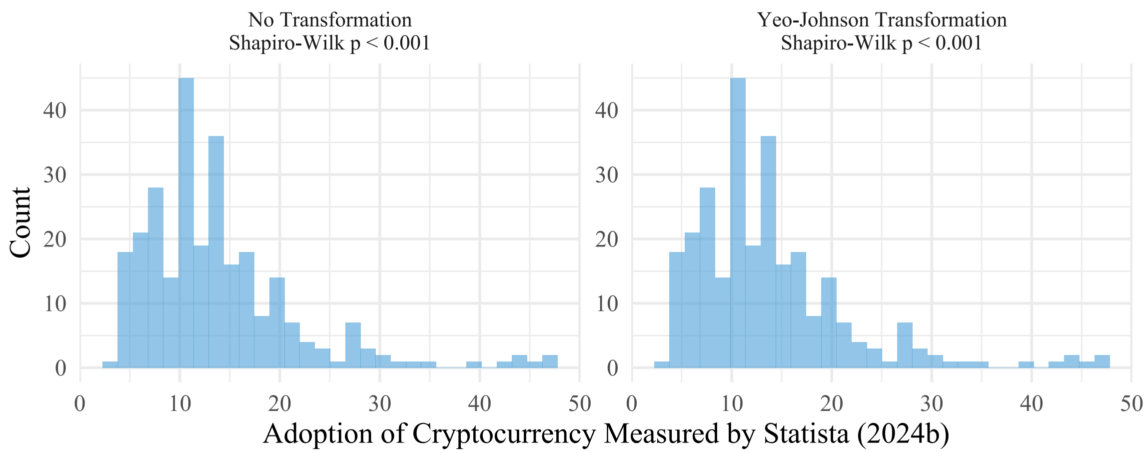

Figure 6: Histograms for Adoption of Cryptocurrency Measured by Statista (2024b)

Figure 7 shows the histograms for the inflation data, the proxy for currency stability. The histogram on the left shows the untransformed inflation data, which is highly right-skewed, with a strong concentration of values near zero and extreme outliers extending beyond 100. Despite a Yeo-Johnson transformation (right panel), the distribution remains non-normal (Shapiro-Wilk $p < 0.001$), though it appears more symmetric and compact, with reduced skewness and a clearer central tendency.

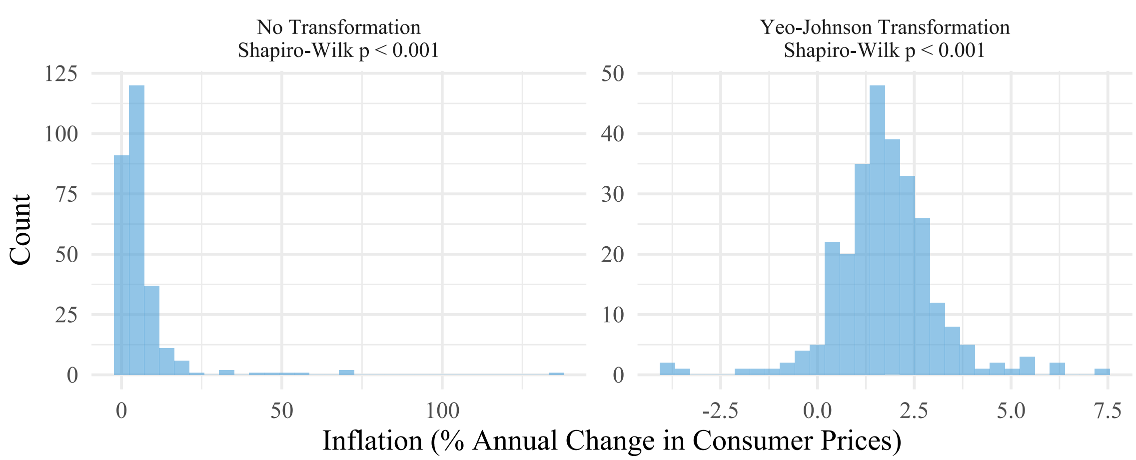

Figure 7: Histograms for Inflation (% Annual Change in Consumer Prices)

Figure 8 shows the histograms for GDS as a percentage of GDP, the proxy for investment. The untransformed GDS data (left panel) exhibits a quasi-normal distribution with a slight right skew and a concentration of values between 20 and 35 and several high-value outliers above 50. After applying the Yeo-Johnson transformation (right panel), the distribution becomes more symmetric and bell-shaped, though the Shapiro-Wilk test still indicates a significant deviation from normality ($p < 0.001$). The transformation reduces skewness and improves the distribution's overall symmetry, although the original distribution was already sufficient for an applied setting, being quasi-normal.

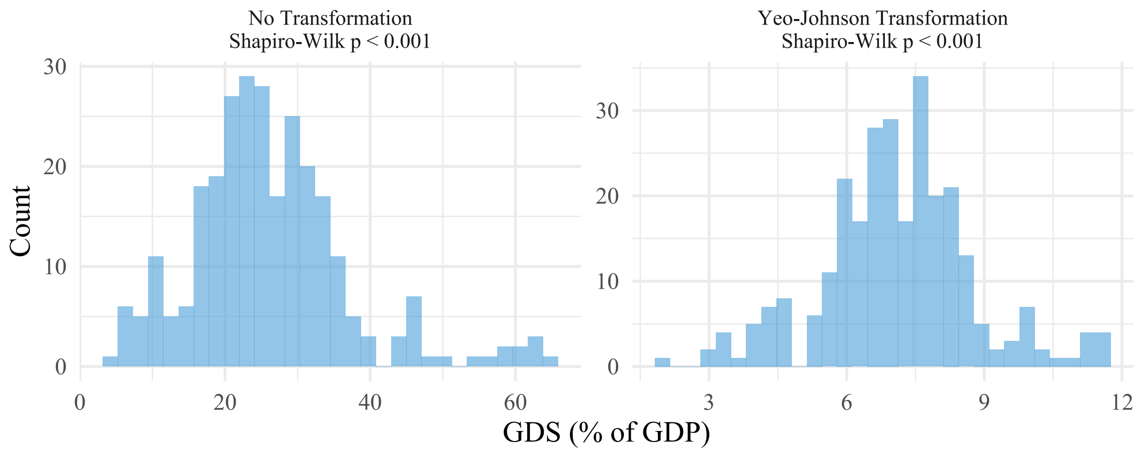

Figure 8: Histograms for GDS (% of GDP)

Figure 9 shows the histograms for GDP per capita, the proxy for wealth. The untransformed GDP data (left panel) shows a combination of a bimodal pattern and a right skew. The two peaks are around the 10K and 50K ranges. There are also outliers above the 75K range. The distribution is not visually improved by the Yeo-Johnson transformation (right panel). The statistically significant Shapiro-Wilks test confirms the non-normality.

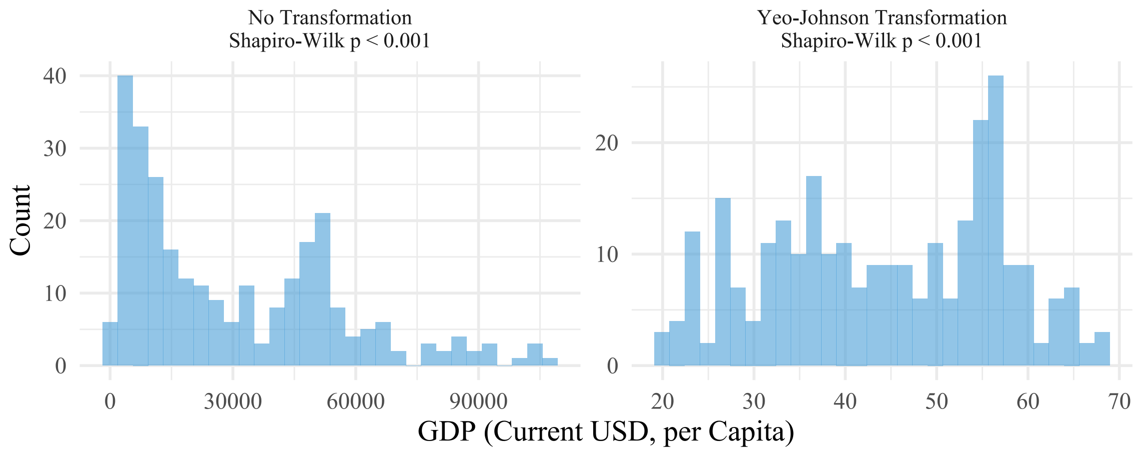

Figure 9: Histograms for GDP (Current USD, per Capita)

Figure 10 shows the histogram for the Political Corruption Index; this is the proxy for sins. The untransformed sins data (left panel) is right-skewed, with most values clustered near zero and a wide spread across the rest of the scale as it moves away from zero in the positive direction. After applying a Yeo-Johnson transformation (right panel), the distribution is not visually improved and becomes bimodal with peaks around the 0 and 0.35 ranges (transformed scale). The Shapiro-Wilk test ($p < 0.001$) confirms non-normality in both cases.

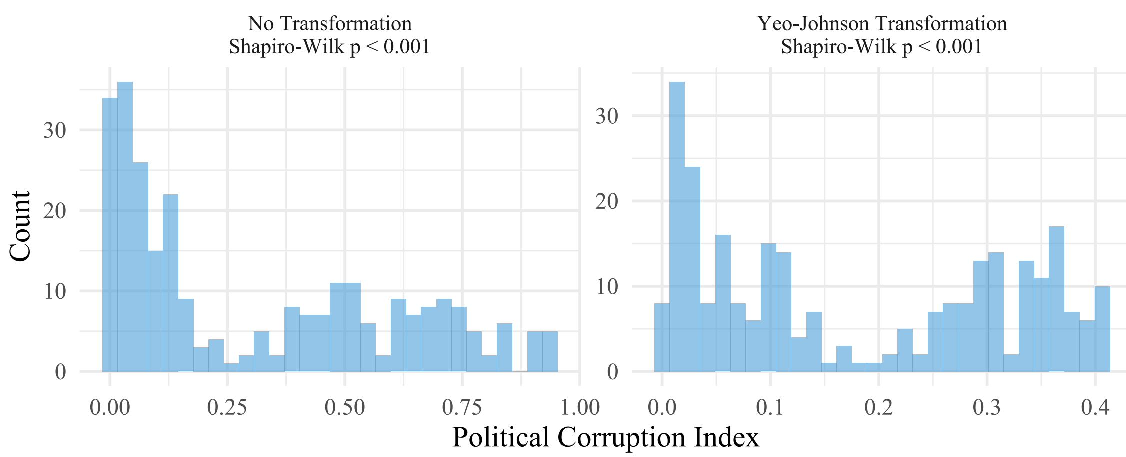

Figure 10: Histograms for Political Corruption Index

Figure 11 shows the histograms for RR as a percentage of GDP; this is the proxy for remittances. The untransformed remittances data (left panel) is right-skewed, with a large spike near zero and a long tail extending beyond 10. The Yeo-Johnson transformation does not improve normality visually. A bimodal peak is created by the transformation. The Shapiro-Wilk test confirms non-normality ($p < 0.001$) in both cases.

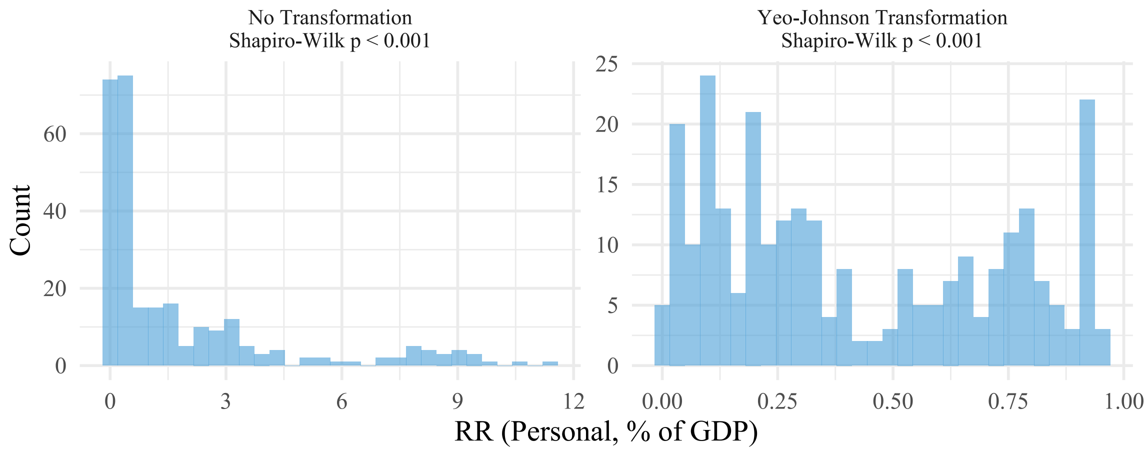

Figure 11: Histograms for RR (Personal, % of GDP)

Figure 12 shows the histograms for the bespoke CC index; this is the proxy for CC. The untransformed CC data (left panel) is right-skewed, with the majority of observations concentrated near zero and a steep drop-off in frequency as values increase. After applying the Yeo-Johnson transformation (right panel), the distribution becomes more compressed and slightly more symmetric but remains non-normal (Shapiro $p < 0.001$). The transformation reduces skewness but does not fully normalize the data. There are values below 0 on the transformed scale due to the small perturbations added to the data to make it compatible with the algorithm conducting the Yeo-Johnson transformation.

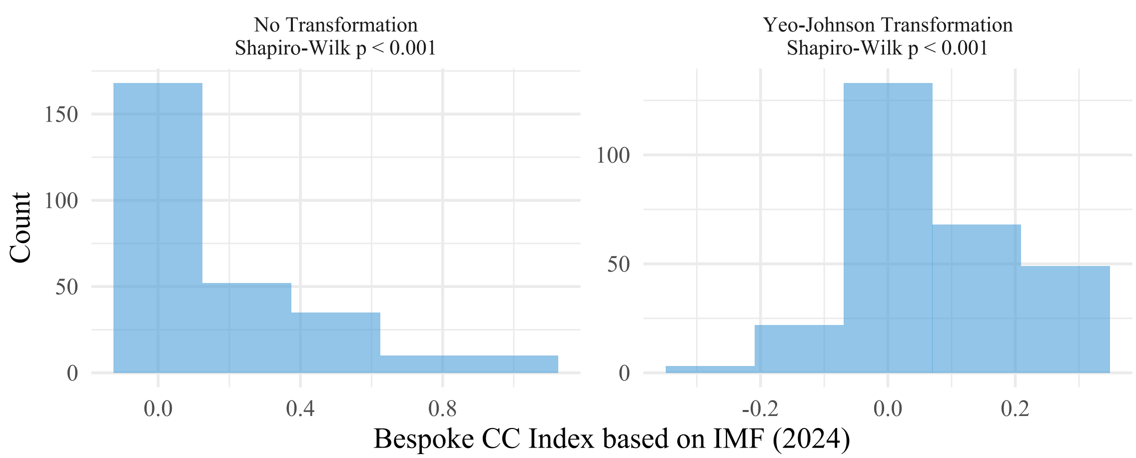

Figure 12: Histograms for Bespoke CC Index based on IMF (2024)

Figure 13 shows the distribution for ED to GDP, the proxy for the risk of sovereign default. The untransformed ED data (left panel) is right-skewed, with a strong concentration of values near zero and a long tail extending beyond 1K. After applying the Yeo-Johnson transformation (right panel), the distribution becomes more symmetric and bell-shaped. The Shapiro-Wilk test shows a weaker deviation from normality ($p = 0.03$), suggesting the transformation improves normality, though non-normality remains.

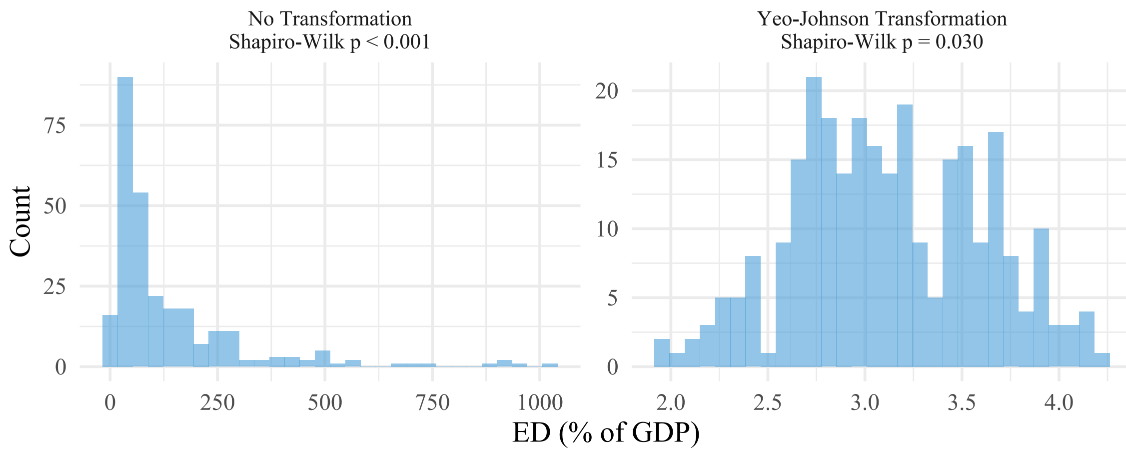

Figure 13: Histograms for ED (% of GDP)

Table 8 shows an overview of the distributions of both the untransformed and Yeo-Johnson transformed variables. The Yeo-Johnson transformation yields a visual improvement in the distribution of four out of the seven transformed variables, even if normality according to the Shapiro-Wilk test is not achieved in any of the variables.

Table 8: Overview of Distributions (With and Without Yeo–Johnson Transformation)

Variable	No Transformation	Yeo–Johnson Transformation
Adoption of Cryptocurrency (%)	right skew	not transformed
Inflation (% Annual Change)	right skew	improved, but non-normal
GDS (% of GDP)	quasi-normal	improved, but non-normal
GDP (Current USD, per Capita)	bimodal and right skew	not improved
Political Corruption Index	right skew	bimodal, not improved
RR (Personal, % of GDP)	right skew	bimodal, not improved
Bespoke CC Index based on IMF (2024)	right skew	improved, but not-normal
ED (% of GDP)	right skew	improved, but non-normal

5.1.2 Correlations of Variables

A correlation matrix visually displays the relationship between two continuous variables. It is important to evaluate this, since an assumption behind the statistical models used in this paper is that there is no multicollinearity, which are correlations between independent variables (Statistics Solutions, n.d.). Figure 14 shows a correlation matrix for independent variables. The numbers inside the cells (as well as their coloring, indicated by the legend) show the Pearson correlation coefficient between two independent variables in the datasets. The variables associated with each correlation can be identified by looking at the row and column of that cell. Please note that the coloring considers only the absolute values of the correlation since if a correlation is positive or negative is irrelevant for the purpose of assessing multicollinearity. The plot shows that most correlations are weak to moderate, with a median absolute value of correlations equal to 0.3 and a maximum Pearson correlation equal to 0.79.[5] This indicates that multicollinearity will not be a problem since even the largest absolute value is below the 0.8 threshold specified in Statistics Solutions (n.d.). The diagonal values of 1 represent the correlation of each variable with itself, which is not relevant for assessing multicollinearity. Please note that each correlation is represented twice (one with a given variable on the x-axis and once on the y-axis).

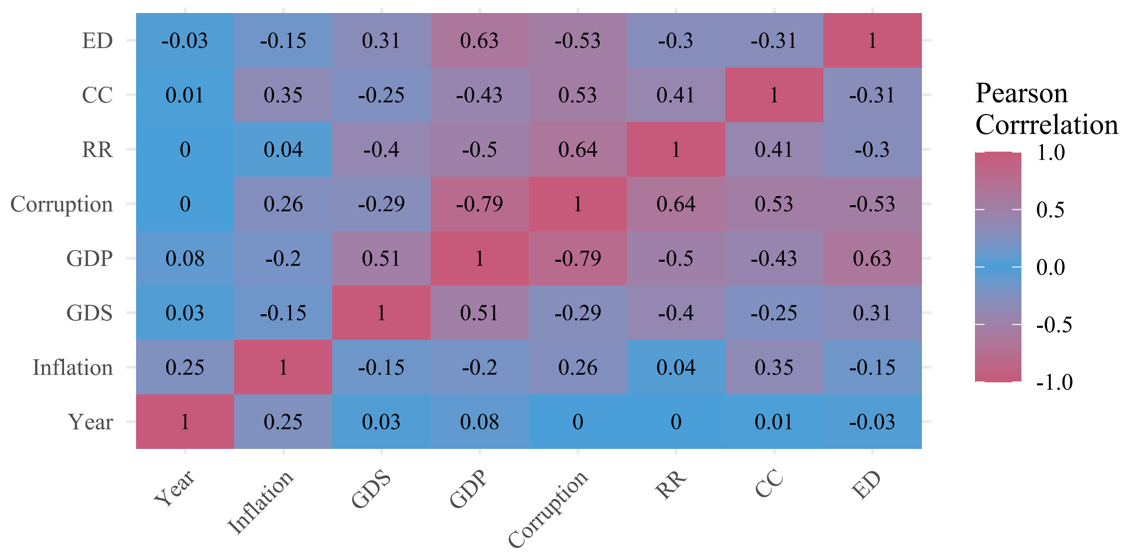

Figure 14: Correlation Heatmap of Independent Variables

5.1.3 Hausman Test

The Hausman test can be used to inform the choice between a fixed or random effects panel data model. A precondition of this is that the observations are randomly drawn from the population (Dougherty, 2011; Qin & Al Amin, 2023). The authors of the Statista (2024b) dataset do not disclose the methodology for selecting the countries. Since the survey was part of the Global Consumer Survey, it can be assumed that the authors made an effort to include a diversity of countries from an economic and political standpoint, due to the title indicating a global focus (Statista, 2020). While looking at the map of countries included in the survey (Figure 4), no immediate category of country is apparent on factors like geographical region, political system or development level. The assumption of random country selection can therefore be considered fulfilled.

Table 9 shows the result of the Hausman test, indicating that the H_0 should be rejected at the p-value of 7.0504762×10^{-8} and that a fixed effects model is preferred over a random effects model (Dougherty, 2011; Qin & Al Amin, 2023).

[5]The summary statistics present here were calculated without the correlation of variables with themselves (diagonal 1s in Figure 14)

Table 9: Results Hausman Test

Chi-Squared	P-Value
46.480	7.050e-08

The paper will now present the statistical results of running these 3 models, as well as a robustness check using a different dependent variable. To determine model quality between Model 1 and 2, both linear regressions, the adjusted R^2 is used. To determine the better model between the best linear regression and the fixed effects models, an F test for individual and / or time effects is used (Qin & Al Amin, 2023).

5.2 Results

This subsection discussed the statistical results of the inferential models. The overviews are presented as tables and figures. For a detailed description of what these tables and figures represent (without interpretations specifically relating to the results), please visit 5.2.5. Readers familiar with statistical methods should be able to understand the results without consulting the guide. The next four subsections present the most important results relevant to the research question, focusing on statistically significant coefficients and indications of model quality. Table 10 shows an overview of the proxies and their associated representations (names) in the results tables.

Table 10: Proxies and Representation in Results Tables

Proxy	Representation in Results
Currency stability	Inflation
Investment	GDS
Wealth	GDP
Remittances	RR
Sins	Corruption
CC	CC
Risk of sovereign default	ED

5.2.1 Model 1: Linear Regression No Transformation

This subsection presents the results of Model 1. Table 11 shows the coefficients of the model. It indicates that the proxies for currency stability, investment and corruption are positively related to the adoption of cryptocurrency, as they have a statistically significant positive estimate at the 10% level. The proxy for remittances is negatively related to adoption and also statistically significant at the 10% level. The estimates for the other proxies: wealth, CC and sovereign default risk are statistically insignificant at the 10% level.

When considering the scale of the independent variables, the sizes of the statistically significant estimates are low, considering the usual yearly changes a country might see in these economic markers. Inflation's estimate is 0.125; this is low considering most countries' inflation rates are unlikely to change by more than two to three percentage points per year. Similarly, the GDS or RR as a percentage of GDP, with their coefficients of 0.1186 and -0.4131, respectively, are unlikely to see large movements in cryptocurrency adoption associated with normal changes in the underlying economic conditions. The coefficient for sins is 15.49, however the underlying dependent variable is on a scale from 0 to 1. This means for a 15.49 percentage point increase in adoption (in the model, no causation implied), a country would have to go from the lowest possible sins value to the highest possible sins value. Under consideration of the range of the underlying independent variable, this effect size is therefore also small. The statistically significant estimates for the linear offsets of the years imply that, relative to the base year, adoption increases by the coefficient estimates' value, in those years where the year coefficient is statistically significant.

Table 11: Model 1 Coefficients

Term	Coefficient Estimate	Standard-Error	T-Statistic	P-Value	Significance
(Intercept)	2.4487	1.4841	1.6499	0.1002	
Year 2020	-0.1627	1.0826	-0.1502	0.8807	
Year 2021	2.1239	1.0849	1.9577	0.0513	.
Year 2022	6.6286	1.1124	5.9586	0.0000	***
Year 2023	7.6670	1.1119	6.8956	0.0000	***
Inflation	0.1250	0.0334	3.7439	0.0002	***
GDS	0.1186	0.0406	2.9174	0.0038	**
GDP	-0.0000	0.0000	-0.1669	0.8676	
Corruption	15.4858	2.4594	6.2965	0.0000	***
RR	-0.4131	0.1930	-2.1405	0.0332	*
CC	-0.9384	1.5444	-0.6076	0.5440	
ED	0.0026	0.0026	1.0033	0.3166	

Table 12 shows the model's summary statistics. The model has an adjusted R^2 of 0.48 - the highest among the two linear regression models tested. Figure 15 indicates heteroscedasticity due to the divergence of residuals as the predicted values increase and therefore issues in the model quality. The distribution of the residuals, as seen in Figure 16 is quasi-normal, with slightly more residuals at the positive end.

Table 12: Model 1 Fit Summary

Metric	Value
Residual Standard Error	5.6709
Multiple R-squared	0.5076
Adjusted R-squared	0.4871
F-statistic	24.6518
Degrees of Freedom (Model)	11
Degrees of Freedom (Residuals)	263
P-Value	0.0000
Residual Min	-15.0243
Residual Q1	-3.3295
Residual Median	-0.2600
Residual Q3	2.3727
Residual Max	21.2960

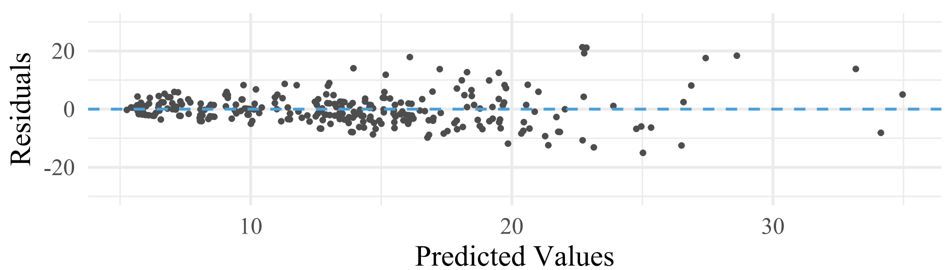

Figure 15: Model 1: Scatter Plot Showing Predicted vs. Residuals

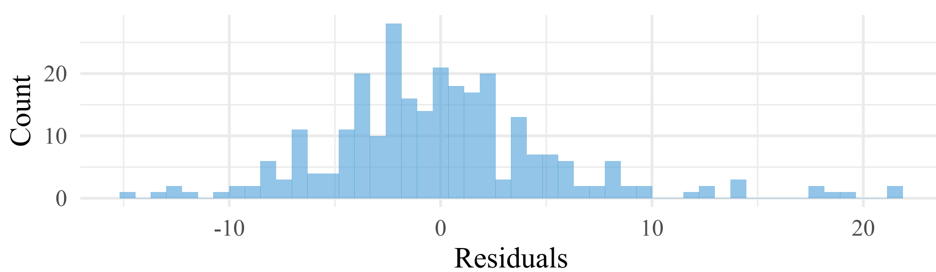

Figure 16: Model 1: Histogram of Residuals

5.2.2 Model 2: Linear Regression Transformations

This subsection presents the results of Model 2 - the linear regression of the Yeo-Johnson transformed quantitative input variables. Table 13 shows the coefficient estimates of the model. It indicates that the proxy for currency stability, savings, sins and sovereign default risk have a statistically significant positive estimate at the 10% level. The proxies for wealth and remittances are negatively related to adoption and also statistically significant at the 10% level. The estimate for the CC proxy is statistically insignificant.

Table 13: Model 2 Coefficients

Term	Coefficient Estimate	Standard-Error	T-Statistic	P-Value	Significance
(Intercept)	-0.6825	5.5591	-0.1228	0.9024	
Year 2020	-0.2802	1.1194	-0.2503	0.8025	
Year 2021	1.9355	1.1275	1.7167	0.0872	.
Year 2022	6.6781	1.2380	5.3942	0.0000	***
Year 2023	8.0265	1.2041	6.6661	0.0000	***
Inflation	0.7261	0.3463	2.0970	0.0370	*
GDS	1.3782	0.2652	5.1964	0.0000	***
GDP	-0.2626	0.0820	-3.2035	0.0015	**
Corruption	18.4614	6.8689	2.6877	0.0077	**
RR	-3.8175	1.5876	-2.4046	0.0169	*
CC	1.5047	3.3891	0.4440	0.6574	
ED	3.1455	1.2200	2.5783	0.0105	*

Table 14 shows the model's summary statistics. The model has an adjusted R^2 of 0.46, slightly lower than Model 1. Figure 17 indicates heteroscedasticity due to the diverging residuals as the predicted value increases and therefore issues in the model quality. The distribution of the residuals, as seen in Figure 18 is quasi-normal, with slightly more residuals at the positive end. Overall, the model quality markers are very similar to Model 1, although Model 1 outperforms Model 2 due to the slightly higher adjusted R^2 value.

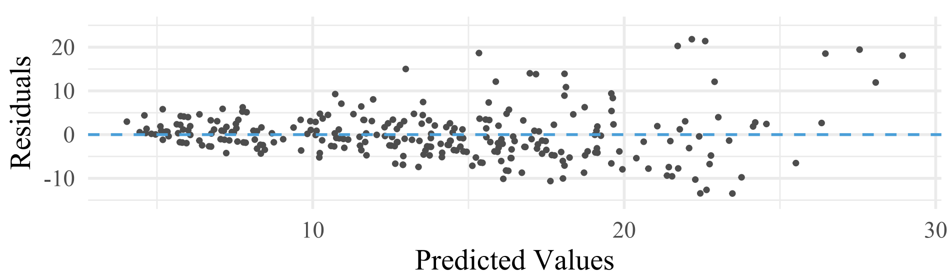

Figure 17: Model 2: Scatter Plot Showing Predicted vs. Residuals

Table 14: Model 2 Fit Summary

Metric	Value
Residual Standard Error	5.8185
Multiple R-squared	0.4817
Adjusted R-squared	0.4600
F-statistic	22.2192
Degrees of Freedom (Model)	11
Degrees of Freedom (Residuals)	263
P-Value	0.0000
Residual Min	-13.4740
Residual Q1	-3.3000
Residual Median	-0.7219
Residual Q3	2.4836
Residual Max	21.8290

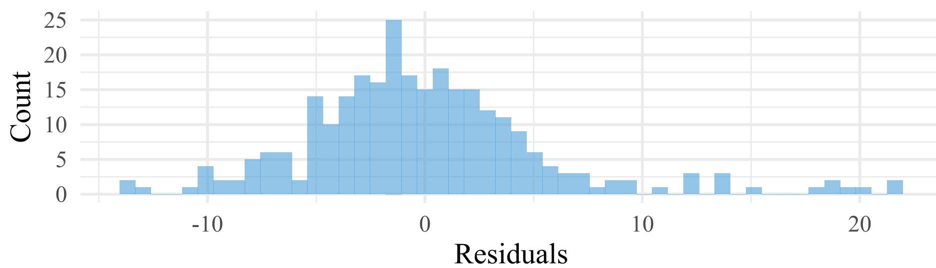

Figure 18: Model 2: Histogram of Residuals

5.2.3 Model 3: Fixed Effects

The fixed effects (Model 3) are presented in this subsection. This model controls for country specific time-invariant characteristics by giving each country a linear offset that can absorb time-invariant characteristics not represented by the data (Dougherty, 2011). These linear offsets can be seen for each country in Table 17. These represent the effect on cryptocurrency adoption of time-invariant characteristics of the countries not modeled by the independent variable (Torres-Reyna, 2007).

Table 15 shows the coefficients of the model. It indicates that the proxies for currency stability and wealth have a statistically significant positive estimate at the 10% level. No other proxies were statistically significant. Although statistically significant, the magnitudes of those estimates are small for both proxies, considering the scale of the predictor variables. Inflation usually fluctuates only by a couple percentage points between years for most countries. Therefore, an estimate of 0.3 for the currency stability proxy means that inflation would have to increase by more than 3 percentage points to increase the percentage points of respondents using cryptocurrency in the Statista (2024b) by 1. Similarly, the GDP per capita would have to increase by over USD 2000 to be associated with a single percentage point increase in cryptocurrency adoption in the Statista (2024b) survey.

Table 15: Model 3 Coefficients

Term	Coefficient Estimate	Standard-Error	T-Statistic	P-Value	Significance
Inflation	0.2950	0.0405	7.2890	0.0000	***
GDS	-0.0945	0.1464	-0.6456	0.5192	
GDP	0.0005	0.0001	5.1142	0.0000	***
Corruption	1.6289	11.5125	0.1415	0.8876	
RR	0.3976	0.7399	0.5373	0.5916	
CC	0.8080	19.2405	0.0420	0.9665	
ED	-0.0086	0.0183	-0.4708	0.6382	

Table 16: Model 3 Fit Summary

Metric	Value
Multiple R-squared	0.3929
Adjusted R-squared	0.2190
F-statistic	19.6910
Degrees of Freedom (Model)	7
Degrees of Freedom (Residuals)	213
P-Value	0.0000
Residual Min	-16.4459
Residual Q1	-1.9994
Residual Median	-0.1958
Residual Q3	1.8935
Residual Max	11.8776

Table 16 shows the model's summary statistics. The fixed effects model cannot be compared directly to linear regressions (Model 1 and 2) using adjusted R^2. Therefore, an F test for individual and/or time effects is used. The test is statistically significant, with a p-value of $1.9144282 \times 10^{-19}$. This means that the fixed effects model is preferred to Model 1 and by extension, Model 2, since Model 1 has a larger R^2 than model 2 (Qin & Al Amin, 2023).

Figure 19 indicates heteroscedasticity due to diverging residuals at the top end of the range and therefore issues with the model assumptions. The distribution of the residuals, as seen in Figure 20 indicates worse heteroscedasticity when compared to Model 1 and Model 2 due to the bimodal distribution. However, since the peaks in the distribution are close together and still centered around 0, this is not a serious issue.

As indicated in Table 17 the fixed effects can be large, considering the scale of the dependent variable. The largest absolute value of a α_i coefficient was 31.9. This is 70% the scale of the dependent variable and represents a considerable effect of unobserved factors. The mean absolute value of the α_i coefficients was 10.4. This represents a mean 10 percentage point difference in adoption of cryptocurrencies as a result of time-invariant country specific factors not modeled by the input variables outside of the country variable.

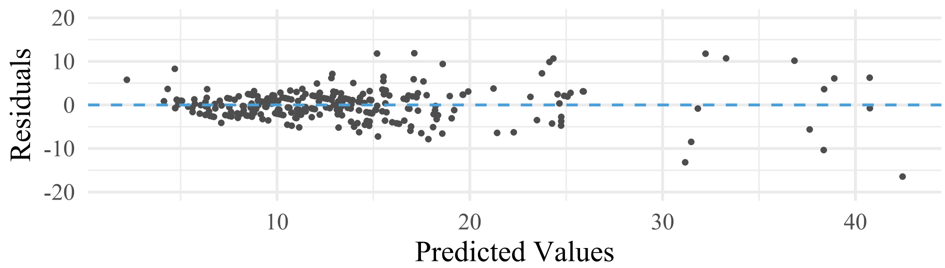

Figure 19: Model 3: Scatter Plot Showing Predicted vs. Residuals

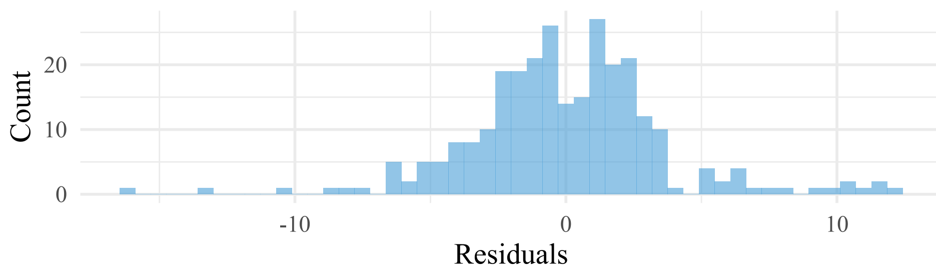

Figure 20: Model 3: Histogram of Residuals

Table 17: Model 3: Country Fixed Effects (Alpha Coefficients)

ARE: 1.18	ARG: -3.03	AUS: -14.81	AUT: -12.37	BEL: -10.27
BRA: 13.33	CAN: -13.04	CHE: -24.02	CHL: 6.93	CHN: 6.04
COL: 10.87	CZE: 0.25	DEU: -12.8	DNK: -11.37	DOM: 3.86
EGY: 3.78	ESP: 0.38	FIN: -13.79	FRA: -10.27	GBR: -10.85
GRC: 6.63	HKG: -3.64	HUN: -0.61	IDN: 15.88	IND: 12.34
IRL: -22.71	ISR: -13.68	ITA: -7.37	JPN: -9.7	KEN: 11.29
KOR: -1.07	LTU: -0.32	MAR: 6.8	MEX: 4.29	MYS: 13.13
NGA: 31.9	NLD: -8.27	NOR: -26.66	NZL: -10.32	PAK: 2.49
PER: 10.67	PHL: 18.05	POL: 0.78	PRT: 2.69	ROU: 1.59
RUS: 3.78	SAU: 5.97	SGP: -11.78	SRB: 1.58	SWE: -16.57
THA: 29.2	TUR: 16.28	USA: -22.9	VNM: 23.48	ZAF: 15.14

5.2.4 Model 4: Robustness Check Using Chainalysis Data

This subsection performs the same statistical tests as Model 3, which was identified as the best due to the statistically significant F test for individual and/or time effects (Qin & Al Amin, 2023). The key difference in Model 4 is the use of a different dependent variable - the ranking of countries on the annually published Chainalysis Geography of Cryptocurrency Report (Chainalysis, 2024).

Data Source Chainalysis is a blockchain data and market research company. They have published their Global Cryptocurrency Adoption Report every year since 2020. It contains a ranking of countries' cryptocurrency adoption. Their methodology is to estimate cryptocurrency adoption by evaluating relevant web traffic for services enabling cryptocurrency transactions. The results are normalized by population and purchasing power (Chainalysis, 2024).

Technical Data Acquisition The data is sourced directly from the reports, as it was not possible to gain access to any web service that could automate the acquisition process. The data was loaded into an Excel file by pasting screenshots into OpenAI's GPT-4o and having the generative model return an Excel file (Chainalysis, 2020, 2021, 2022, 2023, 2024). Manual spot checks were performed. While the data that was present was always correct on the spot checks, the AI model struggled to match countries that were not always consistently named between reports or not consistently available. These errors were sought out and corrected where necessary. However, given the tedious and repetitive nature of this manual task, it is possible that not all errors of this type were found and corrected.

Data Cleaning and Imputation There were 162 distinct countries present in at least one year for the Chainalysis data. The data imputation was done more crudely than for the data used in Model 1, 2 and 3. Data was imputed using country means, even if only one data point was available for a country / indicator. If for any indicator and any country for a given year, no data point was available, this country was removed from the dataset. This left 128 countries in the final cleaned dataset for the robustness check. Readers interested in the summary statistics for the underlying data used in the robustness check should visit Table 25 in Appendix 2. The summary statistics will also be different for the independent variables because the countries evaluated were not the same. Several additional details should be noted:

- The same manual data extensions were performed as for the previous data analysis (see 4.3).
- The data for 2020 presents some countries without a ranking, labeling their adoption as "among lowest" (Chainalysis, 2020, p. 129). These countries were retained by giving them the rank of 143, since 142 was the lowest ranked country in that year.
- The ranking was preferred over the index score since the company stopped giving index in their reports in 2022, providing only a ranking (Chainalysis, 2022, 2023, 2024). While an index could give a more

granular overview of the differences in cryptocurrency adoption between countries, the trade-off of excluding the years 2022 and 2023 would be too severe on data quantity to justify this choice.

Model The final model is akin to Model 3 (details in 5.2.3) with the difference that the proxy for wealth (GDP per capita) was excluded, as this was already considered by Chainalysis in their creation of the index by the decision to normalize the data based on the purchasing power of the country (Chainalysis, 2024). The interpretation guide 5.2.5 can still be consulted. Readers should be aware that the response variable is no longer the same in Model 4. Crucially, the scale of the response variable is conceptually inverted when compared to the Statista (2024b) data. A higher value in the Chainalysis data means a lower rank of cryptocurrency adoption and therefore a lower measure of cryptocurrency adoption. The mathematical model can be seen below. Notice the lack of inclusion of the GDP variable and associated coefficient. The rest is analogous to what was described in 5.2.3.

$$\begin{aligned} Adoption_{it} &= \beta_1 \cdot \text{Currency Stability}_{it} + \beta_2 \cdot Investment_{it} + \beta_3 \cdot Sins_{it} \\ &+ \beta_4 \cdot Remittances_{it} + \beta_5 \cdot CapitalControls_{it} + \beta_6 \cdot \text{Sovereign Default Risk}_{it} + \alpha_i + \varepsilon_{it} \end{aligned}$$

Results Model 4 The results of Model 4 are now shown and discussed. Please note that the α_i values, country fixed effects, are not shown. The mean absolute value of the country fixed effects was 82.86, approximately half the range of the dependent variable. Table 18 shows the coefficients of the robustness check model. It indicates that the proxies for currency stability and sovereign default risk are statistically significant at the 10% level. The coefficient associated with currency stability is 0.1307; this is the size of the within country response of the dependent variable to a one unit change in inflation rate, according to the model. Since a higher value on the response variable (rank of adoption) means a lower adoption of cryptocurrency, conceptually the variable is negatively related - higher inflation means a lower adoption of cryptocurrency. The coefficient associated with the proxy for sovereign default rate is -0.1977. This is the size of the within country response in the rank of cryptocurrency adoption in response to a 1 percentage point change in the sovereign default risk variable. Conceptually this means the concept of sovereign default risk and cryptocurrency adoption are positively related. A higher risk of sovereign default as measured by the ED as a percentage of GDP will be associated with a larger cryptocurrency adoption. For both the currency stability and sovereign default proxies the effect size is small. Several percentage points increases in inflation and ED as a percentage of GDP would be required to see just a single rank within country change in cryptocurrency adoption according to this model.

The proxies for wealth, sins, remittances and CC were statistically insignificant at the 10% level - there is insufficient evidence to reject the null hypothesis that the coefficients for these values are different from 0.

Table 18: Model 4 (Robustness Check) Coefficients

Term	Coefficient Estimate	Standard-Error	T-Statistic	P-Value	Significance
Inflation	0.1307	0.0438	2.9851	0.0030	**
GDS	-0.2240	0.2760	-0.8116	0.4175	
Corruption	42.3520	29.4943	1.4359	0.1518	
RR	0.3313	0.9077	0.3650	0.7153	
CC	-28.7128	41.3477	-0.6944	0.4878	
ED	-0.1977	0.0457	-4.3226	0.0000	***

Table 19: Model 4 (Robustness Check) Fit Summary

Metric	Value
Multiple R-squared	0.0704
Adjusted R-squared	-0.2567
F-statistic	4.77
Degrees of Freedom (Model)	6
Degrees of Freedom (Residuals)	378
P-Value	0.0001
Residual Min	-90.4145
Residual Q1	-8.0980
Residual Median	0.3052
Residual Q3	9.2541
Residual Max	71.8774

Table 19 shows the model's summary statistics. The model has an adjusted R^2 of -0.26. This value indicates that the model is insufficiently informative and not fitted to enough data (Nau, n.d.).

Figure 21 shows the predicted versus residual plot of the robustness check model. The increase in spread of the residuals in the middle of the range of predicted values indicates heteroscedasticity. The size of the residuals is larger than in Model 1, 2 and 3. This alone does not indicate a worse model quality due to the different measurement of cryptocurrency adoption in Model 4. Figure 22 shows the histogram of the residuals for the robustness check model. It indicates an acceptable distribution, with the exception of outliers at the positive and negative end of the residual range, the distribution is quasi-normal.

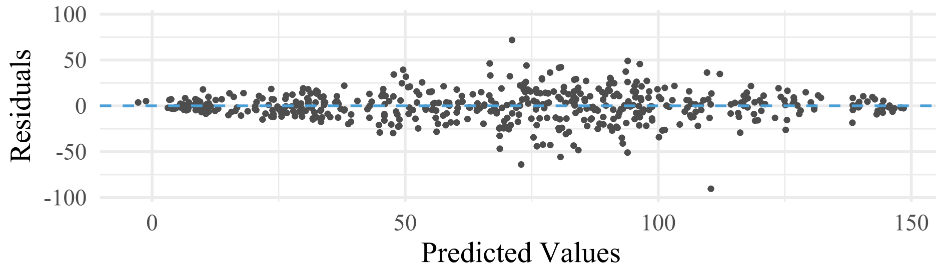

Figure 21: Model 4 (Robustness Check): Scatter Plot Showing Predicted vs. Residuals

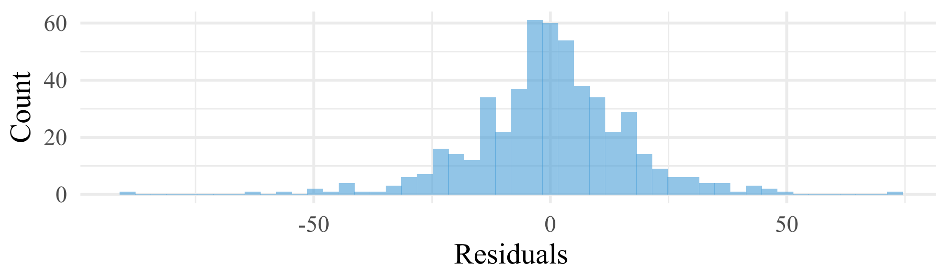

Figure 22: Model 4 (Robustness Check): Histogram of Residuals

5.2.5 Interpretation Guide Tables and Figures for Results

Subsection 5.2 presented 2 types of tables (coefficient table, fit summary table) and 2 types of figures (predicted vs. residual plot, histogram of residual). A guide to their interpretation will be given.

Coefficient Table Tables 11, 13, 15 and 18 present model results in terms of the coefficients of independent variables. The coefficient estimates of the years (only in Model 1 and Model 2) represent linear offsets in the predicted value for the dependent variable for the different years, relative to the reference year, holding other predictors constant. For Model 1 and 2, the coefficient estimates for continuous values represent the expected change in the dependent variable as a result of a one unit change in the respective variable, while holding other variables constant. Note that in the case of Model 2, this refers to a one unit change in the transformed scale, not the original. For Model 3 and 4, the coefficient estimates for continuous variables (all input variables, since there are no categorical inputs), represent the change in response variable as a result of a one unit change in the independent variable while controlling for unobserved, time-invariant characteristics of the country and holding other independent variables constant; this is also known as a *within-country* effect (Torres-Reyna, 2007; Utts & Heckard, 2012; Vaart, 2019). The meanings of the significance column can be seen in Table 20. It is worth noting that at the selected significance level of 10%, even a p-value below 0.1 is sufficient to reject the null hypothesis for a particular variable. In this paper, when interpreting results, no distinction is made between different levels of statistical significance as long as the p-value is below 0.1. The coefficient tables present results to 4 decimal places.

Table 20: Significance Legend for Model Coefficients Tables

Symbol	P-value Threshold	Interpretation
***	$p < 0.001$	Very strong evidence against H_0
**	$0.001 \leq p < 0.01$	Strong evidence against H_0
*	$0.01 \leq p < 0.05$	Moderate evidence against H_0
.	$0.05 \leq p < 0.1$	Weak evidence against H_0
	$p \geq 0.1$	Not statistically significant

It is important to interpret the coefficient estimates while considering the scale of the predictor variable both within a single model's different independent variables but also between models when looking at the same variable, if the scale is different. In the first case, a larger absolute value of a coefficient estimate for one independent variable over another does not mean that proxy has a stronger effect. This is because, for example, it is "easier" for a country to have a one unit (single USD) change in the GDP per capita than a one unit change in the CC proxy (this would imply moving between the maximum and minimum value for the index). In the second case, comparing the same proxy's estimates across models with a different scale, gives no indication of relative strength of the proxy in the model due to the different scales of the proxies resulting from different transformations being applied. This second point is also true when a different response variable is used between models rather than a transformation (Barbanti, 2024).

The standard error measures the estimated standard deviation of a coefficient estimate, indicating the degree of uncertainty. When combined with the estimate, it can be useful to get confidence intervals for coefficients, and check that the direction of effect does not make the estimate change direction within a certain confidence interval. For example if the 95% confidence interval for an estimate is $2 \pm (1.96 * 3)$ then it cannot even be determined which direction the adoption of cryptocurrencies moves in response to a one unit change in independent variable, as this estimate includes a zero and both positive and negative numbers. The t-statistic quantifies this idea by dividing the coefficient estimate by the standard error ($\frac{Coefficient\ Estimate}{Standard\ Error}$) giving a value where a higher number represents greater confidence in the estimate and vice-versa. The p-value is the result of a hypothesis test and represents the probability of obtaining a result at least as extreme as the one observed, assuming the null hypothesis is true. It is used to asses the null hypothesis relating to the coefficient of the predictor variables. At the 10% level chosen for this paper, any p-value below 0.1 indicates the rejection of the null hypothesis that the coefficient of a given variable is different from 0 (Barbanti, 2024; Thieme, 2021; Utts & Heckard, 2012; Vaart, 2019).

Fit Summary Table Tables 12, 14, 16 and 19 show the model's summary statistics. Residuals are the difference between the actual values and the values predicted by the model. Residual standard error represents the standard deviation of all the residuals.

The value for multiple R-squared represents the proportion of variation in the dependent variable explained by the model's independent variables. Please note that in the case of fixed effects models, the variation refers only to the within country variation explained by the model (Torres-Reyna, 2007). Adjusted R-squared is similar, but it adjusts the proportion explained for the amount of independent variables used, penalizing models with a larger number of predictors. Please note that, again, in the case of the fixed effects models (3,4), the variation refers only to the within-country variation explained by the model (Torres-Reyna, 2007). As such, the (adjusted) R-Squared cannot be used to compare model quality meaningfully between linear regressions and fixed effects models.

In models with multiple predictor variables, the f-statistic and p-value do not provide important additional output. These are used to determine whether any of the predictors have an impact on the dependent variable. However, in multiple regressions, p-values from coefficient estimates are usually used for this purpose (Greenwood, 2022; Thieme, 2021).

The degrees of freedom (model) represent the number of β coefficients, excluding the global intercept β_0 (Models 1,2) or country specific offsets α_i (Model 3,4). The degrees of freedom represent the number of observations minus all β coefficients and α_i in the case of Models 3 and 4. The summary statistics residual minimum, residual quartile 1, residual median, residual quartile 3 and residual maximum describe the associated summary statistics of all the residuals for individual observations across years (Thieme, 2021).

Predicted versus Residuals Plot Figures 15, 17, 19 and 21 show a scatter plot demonstrating the value of the response variable that the model predicts a certain country in a certain time would have based on the data (x-axis) and the residual associated with that prediction (y-axis). Recall that the residual is the difference between a prediction and the true value. This means a large residual implies the model did not predict well for this observation. Such a plot is often used to understand the presence of heteroscedasticity. This is a situation where the model is not equally good at predicting the true value across the range of the independent variable; this is undesirable and indicative of the model being unable to capture the true relationships in the phenomena it is attempting to model. In a model that is able to capture true relationships, these scatter plots do not show any discernible visual pattern (Utts & Heckard, 2012; Vaart, 2019).

Histogram of Residuals Figures 16, 18, 20 and 22 show histograms of the residuals. Histograms visually show the frequency at which values appear in certain ranges. One of the assumptions of the types of models used in this paper is the normal distribution of error terms around zero. This means in a model meeting this assumption, most residuals are close to zero, with fewer residuals in frequency brackets further away from zero in both positive and negative directions (Utts & Heckard, 2012; Vaart, 2019; Zicha, 2020).

6 Discussion

The results of the statistical models are largely inconsistent between each other. Table 21 shows an overview of the statistically significant coefficients in the four models. Model coefficients are shown with their associated statistical significance using the symbols presented in Table 20. A dash ("-") for a coefficient means it was not statistically significant. It is important to note that a higher number in the robustness check means that the adoption is lower. For a proxy in Model 4 to have the same direction of effect as a proxy in Model 1, 2 or 3, the signs (+/-) must be inversed in Model 4

The results for the proxies can be divided into four groups based on the direction and statistical significance of their coefficient estimates. The brackets show which proxies are members of which group.

1. Statistically significant effects consistent across two different measures of cryptocurrency adoption (ED).
2. Totally statistically insignificant (CC).
3. Inconsistent direction of statistically significant effects (GDP, inflation).
4. Statistically significant effects consistent across one measure of cryptocurrency adoption only (corruption, GDS, RR).

Table 21: Model Comparison: Significant Coefficients

Term	Model 1: Linear Regression	Model 2: Linear Regression Yeo-Johnson	Model 3: Fixed Effects	Model 4: Robustness Check (Fixed Effects)
(Intercept)	-	-	intercept dropped	intercept dropped
CC	-	-	-	-
Corruption	15.5***	18.5**	-	-
ED	-	3.15*	-	-0.198***
GDP	-	-0.263**	0.000477***	variable not included
GDS	0.119**	1.38***	-	-
Inflation	0.125***	0.726*	0.295***	0.131**
RR	-0.413*	-3.82*	-	-
Year 2020	-	-	not in data	not in data
Year 2021	2.12.	1.94.	not estimated	not estimated
Year 2022	6.63***	6.68***	not estimated	not estimated
Year 2023	7.67***	8.03***	not estimated	not estimated

The first group are predictor variables which had a consistent direction of effect across two measures of cryptocurrency adoption. This group contains only ED. The proxy for sovereign default risk, ED, shows up as statistically significant in two of the four models: Model 2 and 4. The direction of effect is positive in both - the same as originally theorized. Nevertheless, this finding should be taken with caution as the other two models (Model 1,3) do not find a statistically significant correlation and the strength of the effect in Model 4 is low. An increase of 1 percentage point in the ED is associated only with a country moving up (decreasing the rank) in the Chainalysis ranking by around 0.2 ranks. Evidence for a true underlying relationship here is stronger than for the variables in group 4, as is it consistent across two measures of cryptocurrency adoption. The findings in relation to the sovereign default risk proxy are in line with the idea proposed in this paper - that predictors of currency substitution can also explain the adoption of cryptocurrency. Out of all 7 predictor variables, the strongest evidence for an underlying relationship is with the variable, sovereign default risk, taken from the currency substitution literature. It should be stated clearly that this is only one of the two proxies identified from the currency substitution literature. The proxy for currency stability is discussed later in this section.

The second group is those predictor variables that were not statistically significant at the 10% level for any model. This includes only the variable for CC. This means that at the chosen significance level, there is a failure to reject the null hypothesis for all models in the case of the CC variable.

The third group includes predictor variables that did not exhibit a consistent direction of effect across the models. This includes the variables for GDP and inflation. For GDP, this result is contrary to the literature, which confidently identifies wealth as a reason for adoption of cryptocurrency. When comparing the results of this paper to previous studies on GDP as a predictor of cryptocurrency usage, it could be that in this paper no consistent direction of effect was found due to using a global dataset. Previous studies usually focus on subsets of the global population. Lammer et al. (2019) focus on German bank account data. Ricci (2020) studies only the 70 most developed economies. Gemini (2021) focuses on wealthy Americans.

The other variable in the third group is inflation, the proxy for currency stability. No consistent direction of effect was found. This finding does not support the idea that predictors of currency substitution can be used to explain cryptocurrency adoption. Currency stability is identified as a potential driver of currency substitution, but does not consistently explain cryptocurrency adoption in the models tested. This paper adds to the mixed literature relating to cryptocurrency adoption where papers like Choi & Shin (2022), Conlon et al. (2021) and Gaies et al. (2024) find a positive correlation with inflation, and others such as Parino et al. (2018) and Ricci (2020) find a negative correlation. At the data level this means this paper falls into the same category as Phochanachan et al. (2022) who find correlations with inflation under certain conditions only, the conditions in the case of this paper being the different dependent variable used.

The fourth group is those predictors that had a consistent direction of effect but only across one dependent variable. This means evidence for a true relationship is weaker compared to those predictors in group one. These predictors are GDS, corruption and RR. For GDS, the relative weakness of the results is unexpected due to not only cryptocurrency's popularity as an investment vehicle but also because the available literature does confidently identify investment as a use case. The dataset by Glaser et al. (2014) covers a large amount of early global Bitcoin trades. They evaluated the Mt. Gox exchange, which facilitated over 60% of trades taking place during the time period Glaser et al. (2014) studied by (Feder et al., 2017). Nevertheless, other studies such as Voskobojnikov et al. (2020) have the same narrow focus as papers discussed for GDP in the paragraph above, as they focus only on North American respondents and their reasons to use cryptocurrency. In terms of corruption, the results are also weaker than would be expected given the literature. Previous quantitative studies have identified sinful uses as related to cryptocurrency adoption and the anecdotal evidence supports the conclusion (Alnasaa et al., 2022; Macfarlane, 2021; Marmora, 2021). For both GDS and corruption, while the paper does support previous studies showing a relationship to the adoption of cryptocurrencies, the fact that they were only found statistically significant against one dependent variable is contrary to expectations given the strength with which these underlying factors appear in the literature.

The final coefficient in the fourth group is RR. Here, the findings in this paper provide limited quantitative evidence against the idea that remittances are a major driver of cryptocurrency adoption. The variable RR is statistically significant and negatively correlated in two out of four models tested, both using the same dependent variable. The negative correlation is unexpected considering the findings in the literature review showing the potential of cryptocurrency based remittances. However, this finding should be interpreted cautiously. It could reflect a genuine lack of widespread use of cryptocurrencies for receiving remittances, or it could stem from limitations in how adoption is measured, with current data sources potentially missing key forms of usage. This distinction is important because most existing studies focus on the potential for cryptocurrencies to facilitate remittance flows rather than providing empirical evidence that they are actually used in practice. As discussed in the literature review's consideration of remittances (2.2.5), much of the evidence remains anecdotal or theoretical. A few exceptions, such as Rodima - Taylor & Grimes (2019), Metzger et al. (2019) and Robins (2024) provide more grounded insights into current practices. These studies find that while cryptocurrencies (including stablecoins) do play a limited role in remittance ecosystems, the notion of pure crypto-based transactions - where both the sender and receiver use non-custodial wallets - is exceedingly rare. Instead, cryptocurrencies often function as one link in a broader chain involving multiple intermediaries and traditional financial actors on both ends of the remittance transfer.

Further complicating the measurement of cryptocurrency use in remittances is the issue of user awareness and transaction visibility. As highlighted by Robins (2024), many individuals engaged in cross-border transfers may not even realize that cryptocurrency is involved. This is especially true when funds are sent entirely within centralized exchanges. These transactions are settled internally and do not necessarily appear on a public blockchain. As a result, they are effectively invisible to blockchain analysis tools like those used by Chainalysis. Similarly, the lack of user understanding of the fact that cryptocurrencies may be involved in a step of the transaction hinders any survey's ability to capture the adoption. If users do not associate their activity with cryptocurrency use or are unaware that cryptocurrency is involved, they will not report it, leading to systematic underestimation of adoption in remittance-receiving populations. In the case of Chainalysis specifically, another issue in the measurement of remittances comes into play. Their adoption metric is based on blockchain value **received** by centralized services in each country (Chainalysis, 2024). In the situation where an individual gets a remittance transfer paid out to them, the centralized cryptocurrency service provider would not receive any value and therefore this would not show up in the adoption metric of Chainalysis. Due to the non-inclusion of remittances as predictor variables in quantitative analysis of the topic, such as by Parino et al. (2018), Ricci (2020) and Viglione (2015), this paper has still provided a contribution by formally testing the relationship. The only known paper including remittances as a predicting variable is Alnasaa et al. (2022) in a cross-country regression. However, they did not find it to be statistically significant at the 10% level.

This paper will now evaluate strengths and weaknesses of the paper before suggesting future research and making recommendations to policymakers based on the findings.

6.1 Strengths

Two key strengths of this study were the use of panel data and the wide range of countries included in the dataset. Firstly, the panel data setup allows for a more in-depth analysis across both time and geography. By including multiple years for each country, the study can capture how changes within a country relate to changes in cryptocurrency adoption. It also helps control for country-specific factors that don't vary over time but could still influence outcomes - such as legal systems or cultural attitudes toward financial innovation. This improves the reliability of the results and gives the model more explanatory power than a cross-sectional analysis would have.

The second strength is the inclusion of a wide range of countries in the study. Rather than focusing only on high-income economies or one region, this study looks at adoption patterns across many different types of countries - from emerging markets with unstable currencies to more developed economies with established financial systems. This diversity improves the generalizability of the results and makes the findings more relevant for a variety of settings, especially as cryptocurrency adoption continues to grow in places that have not traditionally been the focus of this kind of research. While this is a choice made possible by data availability, this sets the study apart from previous country-level analysis, such as Ricci (2020) focusing only on developed countries.

6.2 Limitations

This paper had several weaknesses. Firstly, as often mentioned already the small data size in the main models using the Statista data as a dependent variable limited not only statistical power, but also the amount of predictor variables that could be included before statistical power would become too low. Additional predictors, or more granular predictions of the existing proxies (such as splitting crime and corruption) could have been useful, but not included due to the adverse effect this would have had on statistical power. The data size was improved in the model using the Chainalysis data as a dependent variable. However, as discussed previously, the Chainalysis data brought with it its own challenges as it is a ranking and provides no indication on the size of the differences between countries. Furthermore, the technical challenges of obtaining this data and resulting skepticism around the accuracy of the manual translation mean that using Chainalysis data as a main dependent variable is unlikely to become a standard in research in its current form. Another weakness was related to the variable for CC. These were sourced from IMF (2024) and turned into an index, bringing challenges. Since only 5 binary components made up the data that would become the index (described in 4.2, the index did not have a normal distribution. The gravity of this issue was attempted to be alleviated using the Yeo-Johnson transformation (see Figure 12). However, random perturbations had to be added to the data to increase variability and use the Yeo-Johnson transformation, limiting the accuracy of the underlying data entering the models. On the Yeo-Johnson transformation, despite this being applied, normality of the data was not achieved and the adjusted R^2 was not improved in Model 2 relative to Model 1. Nevertheless, the distribution was improved as can be seen by the visual changes in 5.1.1.

Another limitation is that while multiple modeling strategies were employed to identify the drivers of cryptocurrency adoption, none of them demonstrated particularly strong explanatory power. The linear regressions demonstrated a maximum adjusted R^2 value of 48%. This is acceptable given that this paper falls within social science research which oftentimes has lower values of this metric compared to papers modelling other processes and there were statistically significant independent variables (Ozili, 2023). Despite an acceptable adjusted R^2 for the linear regressions, the F test for individual and / or time effects did show the fixed effects model superior to the linear regressions. The fixed effects model showed small effect sizes of the coefficient estimates relating to the predictors and less statistically significant predictors than the linear regressions indicating most of the power was carried by the country fixed effects and not the independent variables. This indicates that factors specific to countries not captured in the data used for this paper play an important role - a clear limitation when attempting to explain the adoption of cryptocurrencies.

The final weakness, as with all studies evaluating correlations between variables. The existence of a correlation does not imply one variable causes the other and it should not be interpreted as such. No causality models were employed in this research paper, limiting possible claims that can be made.

6.3 Future Research

Research around cryptocurrency being used for currency substitution should be cautiously encouraged by the results of this paper, suggesting that there might be a link. This theory is underdeveloped in academia and, as such, could benefit from qualitative research using tools like case studies or interviews with users of cryptocurrency susceptible to currency substitution to understand in greater detail any underlying mechanisms that are in place. Once these ideas are concretely defined, statistical methods can be applied to test them.

The findings in relation to remittances encourage further research in the area of cryptocurrency's use in remittances. The existing research clearly argues the potential for remittances, and a limited number of studies have looked at the actual use of remittances. However, the results presented here indicate that being a country that receives remittances may dampen adoption of cryptocurrencies. Is this a result of genuine lack of usage or measurement issues? Future research could attempt to answer these questions by including more granular predictors for countries' remittance markets and financial inclusion such as: number of bank accounts, internet access or regulation around remittances. Such research would allow for more effective regulation from policymakers and potentially entrance into the market by new players looking to provide remittances services with the supposed benefits of cryptocurrency.

Future research both into cryptocurrency being used as currency substitution and cryptocurrencies being used for remittances will benefit from the increased availability of data from the private sector. Previous studies on cryptocurrencies at the country level had to use either cross-sectional data in a single year as was done by Alnasaa et al. (2022) or use technically challenging indicators such as those used by Ricci (2020) and Parino et al. (2018). The regular production of data by both Chainalysis and Statista Global Consumer Survey (through including questions around cryptocurrency use) is a positive development from the perspective of researchers. Nevertheless, these data sources still present issues in terms of scientific rigor. Chainalysis is limited by its discontinuation of publishing the index (at least in the open source versions, it is unclear whether the paid service includes the index rather than just the ranking) and Statista is limited by the limited number of countries (56) included in its survey. When looking at underlying economic factors influencing the use of cryptocurrency, the production of data on the independent variable's side is satisfactory, with the exception of CC and sins data. Factors appearing as relevant in the literature usually have reliable proxies available from either the World Bank or the IMF, even if these are not available for all countries at all points in time. Oftentimes, it is the countries most interesting for the field of dollarization 2.0 and cryptocurrency remittances, which do not have reliable data produced. The same instability that encourages currency substitution or remittances hinders the production of reliable data at the country level. Future research will still be able to use the increasing amount of data to create models with increased statistical power.

As discussed in the limitations, the small number of statistically significant independent variables and large country fixed effects in the fixed effects, mean that there are likely unaccounted factors that this paper, and the broader literature has missed. Future research, particularly qualitative, could attempt to identify additional factors that may be relevant to the adoption of cryptocurrencies. Quantitative models could then test these

6.4 Dollarization 2.0 and Recommendations for Policymakers

A central theme in relation to this paper's findings for policymakers is that macroeconomic factors should not be viewed as a policy lever to stimulate cryptocurrency adoption. Rather, changes in cryptocurrency adoption can be associated with changes in underlying socioeconomic conditions and policymakers should be aware that this potential is there.

For countries that are opposed to the adoption of cryptocurrency, the results suggest that maintaining a low risk of sovereign default through fiscal discipline and preserving credibility with foreign creditors can help limit adoption. These are not new goals; fiscal discipline has been a core objective in many countries, despite recent challenges from economists like Kelton (2020), promoting an agnostic view on the size of domestic currency denominated debts (Kumar & Ter-Minassian, 2007; Rodrik, 2006). In this context, the findings highlight an additional reason to maintain prudent fiscal policy - reducing conditions that are associated with increased cryptocurrency use. In contrast, countries that support cryptocurrency adoption should focus on building strong regulatory frameworks and supportive infrastructure. Attempting to drive adoption by increasing sovereign risk is unlikely to yield positive results and comes with significant dangers. Even economists who question conventional views on public debt do not argue that a sovereign default is a desirable outcome. Rather, they argue that domestic currency denominated debts do not increase the risk of a sovereign default in the first place (Kelton, 2020; Mitchell et al., 2019). The findings related to sins follow a similar logic. Although the data show a positive relationship between sins and cryptocurrency adoption, this should not be interpreted as an endorsement of "using" sins like corruption and criminality as a means to drive cryptocurrency adoption in a country. Instead, countries where sins are "rising" should recognize that such conditions may lead to greater cryptocurrency use and create an appropriate policy response in line with their goals.

Countries with increasing levels of GDS as a share of GDP may experience greater adoption, but the adoption of cryptocurrency is unlikely to take precedence over the broader macroeconomic goal of increasing GDS. Policymakers should be aware of the positive association between GDS as a share of GDP and cryptocurrency while pursuing their policy goals.

7 Conclusion

This study has conducted an econometric analysis of underlying factors predicting the adoption of cryptocurrency at the country level. Underlying factors found as relevant in current research (currency stability, investment, wealth, sins, remittances and CC) were augmented with a proxy for the risk of sovereign default. The choice of this additional predictor was informed by the idea that the new technology of cryptocurrency could serve as currency substitution for two main reasons. Firstly, due to the relative ease of transferring funds when compared to using traditional financial institutions or cash. Secondly, due to the possibility of cryptocurrencies being more stable than fiat currencies depending on the inflationary and exchange rate context. Currency substitution's only predictor not already considered by the cryptocurrency adoption research is the sovereign default risk - which is why this was included in this paper.

The statistical analysis covered four models with two different measures of cryptocurrency adoption. Model 1, 2 and 3 used data by Statista (2024b). Model 4, used as a robustness check of the results, used data by Chainalysis (Chainalysis, 2020, 2021, 2022, 2023).

The results uncovered a relationship in two (Model 2 and 4) out of four models between the proxy for sovereign default risk and cryptocurrency adoption. The idea that there may be a true underlying relationship is supported by the fact that the ED predictor was the only one with a statistically significant effect in the same direction in two models using a different proxy of cryptocurrency adoption. However, two other models (Model 1 and 3) did not find a statistically significant relationship, which requires these results to be taken with caution. The results in relation to the sovereign default risk proxy support the idea that the factors driving currency substitution also drive the adoption of cryptocurrency. Not all of the results support that idea however - the direction of effect for currency stability, which is also identified as a predictor of currency substitution, was not consistent, when the associated variable was statistically significant. The evidence presented by the literature on currency stability being related to the adoption of cryptocurrency is already mixed. The inconsistent results of this paper in relation to currency stability add further mixed evidence to the literature field on cryptocurrency adoption. Proxies for sins, investment and remittances were also found to be statistically significant in two models; however, these were only consistent across one measure of cryptocurrency adoption, weakening the evidence for a true underlying relationship. The proxy for remittances was negatively correlated to measures of adoption in two models, with no relationship uncovered in the other models. This contradicts much of the available research into remittances as a driver of adoption. It is possible this was due to measurement issues or a genuine lack of application for cryptocurrencies in the remittance industry. The proxy for CC was statistically insignificant for all models, suggesting this factor is not connected to the adoption of cryptocurrency.

This paper has attempted to contribute to the literature field on cryptocurrency adoption and currency substitution. The former field was expanded via the inclusion of sovereign default risk. The latter field was expanded by providing an analysis typically done on foreign currencies for cryptocurrencies. Both of these approaches were novel. The inclusion of sovereign default risk provides results encouraging further research in the area of dollarization 2.0, despite the proxy not being related to cryptocurrency in all models. Research would benefit from clearly defined theoretical mechanisms to inform the quantitative analysis of the increasing amount of data on cryptocurrency adoption.

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Appendix 1: Structured List of Literature

This appendix gives a visual overview of the two main important fields of academic literature for this paper: Drivers of currency substitution and drivers of cryptocurrency adoption.

Literature Area 1: Drivers of Currency Substitution

Table 22 below shows the overview of the key literature on currency substitution and in relation to this research. It is a visual representation of the text in 2.1. Please note while not explicitly included in the literature review, the adoption of new technology as a driver of currency substitution is discussed in 1.5.

Table 22: Visual Summary Currency Substitution Literature

Theme	Viewpoint	Author	Methods	Concrete Findings
Currency Stability: Inflation	positive effect	Vieira et al. (2012)	quantitative panel data study of 72 economies	inflation is a predictor of currency substitution; however, the risk of sovereign default was an even stronger predictor
Currency Stability: Inflation	positive effect	Rennhack & Nozaki (2006)	quantitative panel data study of 62 economies	currency substitution is a response to inflation, currency depreciation
Currency Stability: Inflation	positive effect	Honig (2009)	quantitative study of 66 – 92 (depending on model) countries	lack of trust in the stability of the local currency increases currency substitution
Currency Stability: Inflation	positive effect	Kokesnyne et al. (2010)	literature review qualitative	countries wishing to stop currency substitution should focus on taming inflation
Currency Stability: Inflation	positive effect	Taşseven et al. (2015)	case study – Turkey	argues foreign currency was used instead of the Lira due to the high inflation
Currency Stability: Inflation	positive effect	Levy (2021)	narrative	the author credits the reduction in inflation as the reason behind the success of Latin America's attempts to reduce inflation
Currency Stability: Inflation	no effect	Stix (2011)	quantitative study of household data of Croatia, Slovakia, Slovenia	neither inflation expectations nor exchange rates were a predictor of currency substitution
Currency Stability: Exchange Rate Volatility	positive effect	Ajibola (2020)	quantitative case study – Nigeria – autoregressive distributed lag	exchange rate volatility was positively correlated to currency substitution
Currency Stability: Exchange Rate Volatility	positive effect	Ju (2020)	threshold ARCH model studying 28 economies	significant positive correlation between currency substitution and exchange rate volatility
Currency Stability: Exchange Rate Volatility	no effect	Stix (2011)	quantitative study of household data of Croatia, Slovakia, Slovenia	neither inflation expectations nor exchange rates were a predictor of currency substitution
Sovereign Default	positive effect	Vieira et al. (2012)	quantitative panel data study of 72 economies	inflation is a predictor of currency substitution; however, the risk of sovereign default was an even stronger predictor
Technology	positive effect	Ujunwa et al. (2021)	quantitative case study - Nigeria	financial innovation found to be a significant predictor of currency substitution in Nigeria between 2005 – 2019
Technology	positive effect	Guidotti (1993)	theoretical model	by reducing the cost of transacting and holding foreign currencies, technological innovation can increase the usage of foreign currencies

Literature Area 2: Drivers of Cryptocurrency Adoption

Table 23 below shows the overview of the key literature on the adoption of cryptocurrencies in relation to this research. It is a graphical representation of the text in 2.2.

Table 23: Visual Summary Cryptocurrency Adoption Literature

Theme	Viewpoint	Author	Methods	Concrete Findings
Inflation	positive effect	Conlon et al. (2021)	quantitative – time series – continuous wavelet transform	Bitcoin price and US 5 year forward inflation expectation are positively correlated, however only during crisis times
		Choi & Shin (2022)	quantitative – time series – vector autoregression at weekly frequency	findings suggest a positive relationship between Bitcoin prices and inflation
		Taskinsoy (2019)	case study – Turkey	Bitcoin use in Turkey has been driven by inflation of the domestic currency
	mixed / no effect	Phochanachan et al. (2022)	quantitative – time series – markov switching vector autoregression	Bitcoin can positively correlate to inflation, in the short term, the study focused on high cryptocurrency adoption countries only
		Gaies et al. (2024)	quantitative – time series	Bitcoin prices increase in response to inflation, under conditions of uncertainty
		Smales (2024)	quantitative – time series	above 2% inflation expectation sees no co-movement with Bitcoin, under 2% inflation it does
		Basher & Sadorsky (2022)	quantitative – time series	Bitcoin is not a good hedge against inflation as there is no co-movement
	negative effect	Parino et al. (2018)	quantitative – cross country	negative correlation between inflation in countries and their Bitcoin adoption, data only before 2015
		Ricci (2020)	quantitative – cross country	negative correlation between inflation in countries and their Bitcoin adoption, only data for developed economies in their study
Investment	positive effect	Voskobojnikov et al. (2020)	interviews	investment is the primary intended use of non-users of cryptocurrency
		Glaser et al. (2014)	account level quantitative analysis	users on a sampled exchange (Mt. Gox) shuffled funds mostly between themselves and not outside the exchange, indicating investment, not payment was the intended use
Wealth	positive effect	Lammer et al. (2019)	account level quantitative analysis	looking at a German bank's accounts; wealthier individuals were more likely to buy Bitcoin
		Parino et al. (2018)	quantitative - cross country	GDP per capita correlated positively with Bitcoin adoption
		Gemini (2021)	non-representative survey - US	average cryptocurrency holding respondent has a household income approximately 1.5 times the national average
Sins	payment for illicit goods is a reason for using cryptocurrency	Marmora (2021)	quantitative – panel data	national Bitcoin trading volume is positively correlated to marked shocks in the shadow economy (raids, seizures), indicating illicit use
		Saurabh (2017)	anecdotal	there are websites, such as Silk Road where people can buy outlawed goods online and pay using Bitcoin
	cryptocurrencies are being used to evade sanctions	Sarvi (2020)	case study – Iran	Bitcoin is a suitable cryptocurrency for Iran to use in evading international sanctions.
		Chainalysis (2020)	authors provide just data; conclusion is drawn	75% of trades at a random Venezuelan exchange were over USD 1000 (suggesting elites were trading)
	corruption	Carlson (2016)	interview of experts on Argentina	Argentina's history of corruption fosters the use of Bitcoin
		Alnasaa et al. (2022)	quantitative – cross country	corruption is positively associated with cryptocurrency adoption
Remittances	positive effect	Folkinshteyn et al. (2015)	case study	Bitcoins properties make it suitable for use as a low-cost remittance payment system
		BBC (2021)	anecdotal	El Salvador's official reason for adopting Bitcoin as legal tender was to reduce money being lost to fees as emigrated El Salvadorians send money back into the country
		Ruchti (2019)	case study	argues that Libra had the potential to increase financial inclusion of the unbanked through integration with communication platforms
	no effect	Alnasaa et al. (2002)	quantitative – cross country	no association between remittances and cryptocurrency adoption
Capital Controls	positive effect	Carlson (2016)	interview of experts on Argentina	capital controls drive the use of Bitcoin in Argentina
		Viglione (2015)	quantitative – cross country	countries with capital controls see a premium on Bitcoin prices, which authors interpret as extra demand
		Hu et al. (2021)	quantitative	25% of Bitcoin trading volume in China was capital flight
		Alnasaa et al. (2022)	quantitative – cross country	capital controls are positively related to cryptocurrency adoption

Appendix 2: Missing Data Patterns

This section shows the missing patterns for the pre-imputation data of all variables with the exception of the CC index, as this was already presented in the section 4.3. Please see 4.3 for a guide on how to interpret the figure.

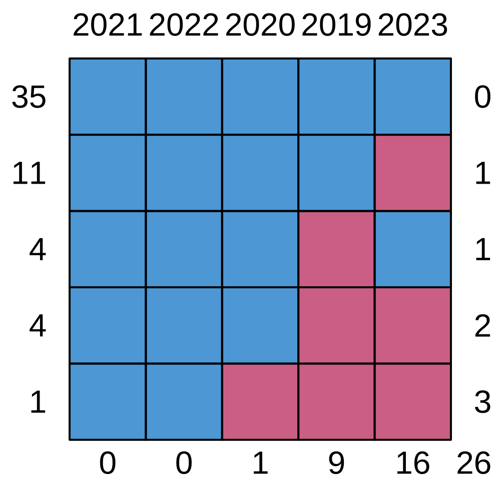

Figure 23: Missing Pattern for Adoption of Cryptocurrencies Measured by Statista (2024b)

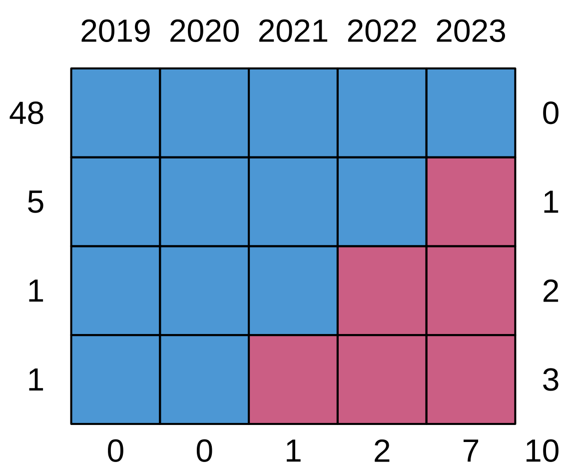

Figure 24: Missing Pattern for GDS (% of GDP)

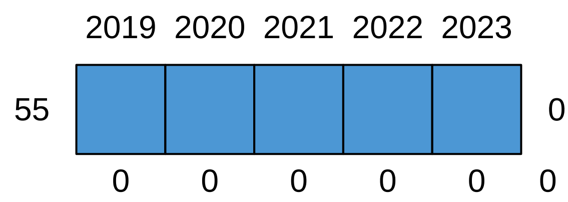

Figure 25: Missing Pattern for GDP (Current USD, per Capita)

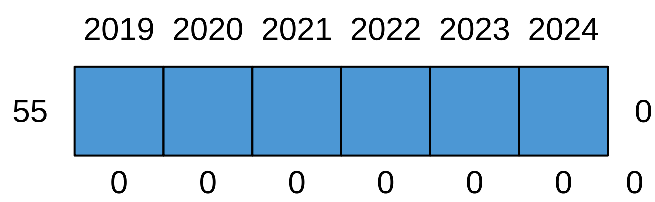

Figure 26: Missing Pattern for Political Corruption Index

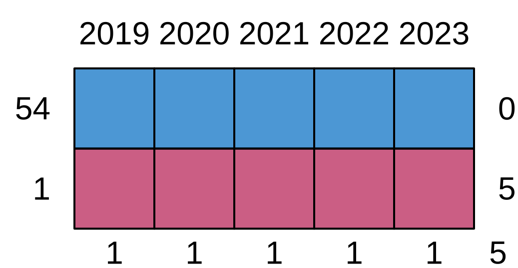

Figure 27: Missing Pattern for RR (Personal, % of GDP)

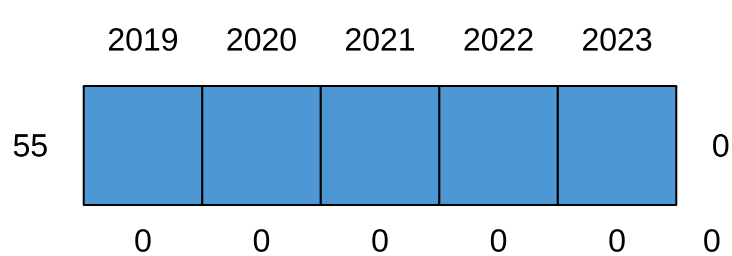

Figure 28: Missing Pattern for ED (% of GDP)

Appendix 3: Summary Statistics

Table 24 shows the summary statistics for the data of the 55 countries used in the models considering the Statista data as the dependent variable.

Table 24: Summary Statistics for Data Used With Statista Set

Variable	Mean	Median	SD	Min	Max
Adoption	1.374182e+01	1.200000e+01	7.918073e+00	3.000000	47.00000
Inflation	6.355795e+00	3.495058e+00	1.199331e+01	-2.093333	133.49000
GDS	2.615827e+01	2.459985e+01	1.090300e+01	3.433016	64.10049
GDP	3.016456e+04	2.224241e+04	2.575058e+04	1322.314785	108798.45117
Corruption	3.107382e-01	1.630000e-01	2.925078e-01	0.002000	0.93900
RR	1.756200e+00	4.651821e-01	2.553642e+00	0.000000	11.39899
CC	1.723636e-01	0.000000e+00	2.762494e-01	0.000000	1.00000
ED	1.380045e+02	6.940000e+01	1.719735e+02	9.000000	1033.00000

Table 25 shows the summary statistics for the data of the 128 countries used in the model considering the Chainalysis data as the dependent variable. The reason that the maximum value, 152, for the Chainalysis value (the ranking of the country in terms of adoption of cryptocurrencies) is higher than the number of countries is that some countries were removed due to insufficient data in the data preparation.

Table 25: Summary Statistics for Data Used With Chainalysis Set

Variable	Mean	Median	SD	Min	Max
Chainalysis	6.905029e+01	68.000000	4.116841e+01	1.000000	152.00000
Inflation	1.204457e+01	4.903386	3.750264e+01	-2.595243	557.20182
GDS	2.228550e+01	22.183888	1.446653e+01	-44.005549	67.63477
GDP	1.870759e+04	6951.712523	2.455873e+04	352.603733	133711.79444
Corruption	4.453867e-01	0.478000	3.003933e-01	0.002000	0.94700
RR	4.241659e+00	1.651115	6.279202e+00	0.000000	32.56354
CC	2.769531e-01	0.200000	3.285741e-01	0.000000	1.00000
ED	1.128833e+02	61.300000	1.641342e+02	2.500000	1115.00000

Appendix 4: GitHub Access

This project and associated data can be found on a public GitHub repository: click here.

If there are any issues with the access, please contact the author via the following e-mail: vayloyanalec49@gmail.com.

Appendix 5: Reflecting on the Use of Artificial Intelligence

This project heavily leveraged AI. The single largest and most suitable use case was for generating code and solving coding issues. Being able to generate a working solution from only the input structure and desired output saved considerable time and effort. Unlike previous projects, I did not attempt to write code from memory or use non-AI sources. Partly, this was due to time constraints, but also because I felt confident in my ability to verify that the code did what I intended by evaluating the output or performing smaller intermediate steps to (hopefully) ensure mistakes did not carry forward.

For the creation of the cover image, OpenAI's GPT-4o was used.

I also used AI to draft some sections or provide inspiration to get started. While the generated passages were not satisfactory on their own, I found it much easier to revise the provided sections into what I wanted, rather than starting from scratch. In that sense, the AI was successful. For certain sections I also wrote a section and then gave it to the AI to improve flow and clarity. In this use case an issue was that when pasting back into the markdown documents, dynamic objects like headings, references and formulas oftentimes were not recognized by the markdown as such. This limited the practical use of this approach.

I used various spellcheckers: the built-in ones in RStudio and Microsoft Word (after converting the knitted .pdf to .doc). I did not find that pasting the PDF into an AI chat bot reliably caught spelling, let alone grammar, errors. Dedicated spell-checking software in writing tools definitely outperformed AI in this aspect. LanguageTool.org was used for smaller sections. What did work was for smaller sections not requiring formatting and latex / markdown references, to paste a whole section, and having a Generative AI (so not dedicated spelling software) correct the spelling - this was done since it is much faster than knitting and converting to a .doc.

I attempted to use AI for research as well; however, this did not work well. The models frequently invented studies that I was never able to verify on common research platforms. Blindly relying on such information would have been disastrous. Since academic work requires citations, such mistakes are unlikely to go unnoticed by the author.

In the preliminary study, when I was unsure of the data available for CC, I proposed another use case, which ultimately was not needed. It is still unlikely that it would have worked to a satisfactory degree. The idea was to fill out an empty table consisting of country rows and year columns with socioeconomic data. By running a loop over the rows and columns, the relevant country and year could be extracted and used in a web service call with a prompt to an AI model. The prompt would then look something like: "Give me an estimate of the severity of CC from 1 (least severe) to 10 (most severe) in [Switzerland] in [2023], use a global comparison for the rating and return only the number, no comments." This worked from a technical standpoint during testing for the preliminary study. However, the results were inconsistent (when run multiple times) and often did not provide the most recent data. This made that data collection approach impractical, beyond the fact that Generative AI cannot be referenced or reproduced in the first place and is therefore incompatible with academic standards. At a larger scale, it would also have been costly. I made roughly 500 calls to the web service, which resulted in a cost of around CHF 5. For big data applications with millions of rows, costs would likely become prohibitive.

The generative models used were the most recent versions by OpenAI and less frequently, Gemini.