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International Review of Financial Analysis 103 (2025) 104217

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

# Economic and financial development as determinants of crypto adoption

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ARTICLE INFO

*JEL codes:*
G15
C33
C45
I25

*Keywords:*
Cryptocurrency adoption
Financial inclusion
Economic development
Panel data
Machine learning

ABSTRACT

This research investigates the macroeconomic determinants of crypto adoption, illuminating the potentials of cryptocurrencies to accelerate financial inclusion. By exploiting an extensive dataset from 165 countries between 2019 and 2021, this study employs various econometric methodologies, including Panel Feasible Generalized Least Squares (PFGLS), Robust Least Squares (RLS), and Quantile Regressions (QR). These classic econometric techniques are complemented by several machine learning techniques such as Bagging, Boosting, and Support Vector Machine (SVM) regressions, as well as Artificial Neural Networks (ANNs) and Naïve Bayes (NB) classification algorithms. The results show an interesting trend: cryptocurrency adoption is more prevalent in countries with robust financial markets and higher education levels. This suggests that crypto adoption is primarily a byproduct of sophisticated financial environments and an educated population, rather than a direct facilitator of financial inclusion.

## 1. Introduction

Financial inclusion is much more than an economic buzzword; it is an important objective that carries wide implications. It is about making accessible basic and affordable financial products and services that cater to the needs of individuals and entities. Financial services, such as banking, lending, equity, and insurance, are not just conveniences but also prerequisites for economic growth and poverty reduction. Financial development has historically played a significant role in promoting economic growth and prosperity by enhancing the efficiency of financial institutions, markets, and instruments. However, recent studies suggest that the positive impact of traditional financial development on economic prosperity has been diminishing since the 1980s (Valickova et al., 2015).

Financial inclusion is an important aspect of financial development, which ensures that all segments of society, especially the underserved and marginalized, have access to affordable financial services. The concept of financial inclusion has evolved significantly over the decades, increasingly aligning with broader global development agendas. This shift became particularly pronounced with the introduction of the Sustainable Development Goals (SDGs) by the United Nations (UN) in 2015, which established the importance of inclusive economic growth in a holistic framework. Specific SDG targets reduce inequality, foster decent economic growth, and create an inclusive economic environment. In this regard, financial inclusion plays a crucial role in achieving sustainable and equitable development worldwide (Kara et al., 2021). Digital technologies have recently revolutionized the financial services landscape, offering innovative solutions to expand financial access. For instance, digital payments (Demirgüc-Kunt et al., 2022) and mobile money services (Ahmad et al., 2020) have accelerated financial inclusion in developing countries by reducing transaction costs and overcoming geographical barriers. Further technological advancements, such as blockchain, cryptocurrencies, and other crypto assets, have the potential to act as catalysts for both financial development and inclusion by significantly reducing the costs of financial services and broadening access. Patel et al. (2022) highlight that adopting blockchain technology can dramatically lower financial service costs, thereby expanding access. Additionally, blockchain and cryptocurrencies may mitigate the effects of economic policy uncertainty, contributing to more stable financial environments (Demir et al., 2018). Nevertheless, these

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https://doi.org/10.1016/j.irfa.2025.104217
Received 16 June 2024; Received in revised form 30 October 2024; Accepted 28 March 2025
Available online 1 April 2025

innovations present new challenges. Yue et al. (2022) emphasize that the complexities introduced by new financial instruments can exacerbate personal financial risks. Concurrently, Khera et al. (2022) draw attention to societal implications, particularly the risk of a digital divide where segments of the population may be left behind due to limited access to or understanding of new technologies.

While existing studies investigate the macro-level drivers of cryptocurrency and blockchain adoption in financial contexts (Foley et al., 2022; Wong et al., 2020), a direct linkage between such drivers and broader economic welfare or financial inclusion remains largely unexplored. El-Morshidy et al. (2024) investigate crypto adoption with a survey on the example of Kuwait. In particular, they find that perceived usefulness and perceived ease of use are positively related to consumers' acceptance of cryptocurrencies. Wahyuni et al. (2024) confirm that US macroeconomic variables can be significant predictors of the Bitcoin price. Saiedi et al. (2021) come close to the direction we aim for by examining global drivers of cryptocurrency infrastructure adoption, concluding that crypto adoption is driven by failing traditional financial systems and its potential use as a reserve currency. Finally, Nguyen and Nguyen (2024) present a framework of overall technological adoption predictors, encompassing several economic, financial, political, and cultural aspects. Among various factors, they find that Gross Domestic Product (GDP) per capita only plays a limited role in crypto adoption.

Despite these valuable contributions, several important gaps remain in the literature. First, there is a scarcity of multi-country panel studies that examine the macro-level drivers of cryptocurrency adoption, especially their linkage to broader economic welfare and financial inclusion. Second, critical development economics factors such as electricity prices and educational levels have not been thoroughly explored in the context of cryptocurrency adoption. Lastly, previous studies have often employed specialized methodological approaches, lacking advanced econometric techniques due to data scarcity and methods to identify potential nonlinear relationships.

To address these gaps, our study exploits a multi-country panel dataset to examine the impact of macroeconomic determinants on crypto adoption across 165 countries from 2019 to 2021. We use the cryptocurrency adoption index annually, as reported by Chainalysis, to capture the crypto adoption within a country. The core of the analysis is anchored in applying the Panel Feasible Generalized Least Squares (PFGLS) estimator, which provides a robust foundation, including potential heteroskedasticity and autocorrelation. Moreover, we further employ Robust Least Squares (RLS), Quantile Regression (QR) techniques, and sample splits, which offer additional insights into the direction of the relationship between cryptocurrency adoption and macroeconomic indicators, allowing us to go beyond most preliminary studies. To ensure the robustness and reliability of previous findings, several Machine Learning (ML) techniques are applied.

While keeping the relevant benchmark variables from prior research, we contribute to the literature as we place a particular emphasis on financial development and other development economics factors such as electricity prices and educational levels. Furthermore, we employ a robust set of methodologies, including several sample splits and advanced techniques to identify potential nonlinear relationships.

The paper is organized as follows. Section 2 thoroughly reviews the existing literature and establishes the study's theoretical foundation, highlighting the novel contributions reached by this research. In Section 3, the methodological framework employed in the analysis is carefully outlined. Section 4 introduces the dataset and thoroughly examines the selected series. The core empirical results are explored and interpreted in Section 5, while Section 6 is dedicated to validating the robustness of previous panel data findings through advanced ML techniques. The paper ends with Section 7, which synthesizes the insights from the analyses into actionable policy recommendations.

## 2. Literature overview

It is necessary to connect several literature directions to get a comprehensive picture of the approach followed in this research and to lay a solid foundation. Therefore, we organize this section into three focused streams to provide a thorough understanding of the interplay between financial inclusion, technological advancements, and cryptocurrency adoption. The first stream examines the role of financial inclusion in economic development and prosperity, highlighting its significance and impact on global economies. The second stream explores the influence of technology – especially blockchain – on enhancing financial inclusion and the intricacies of finance research related to cryptocurrencies. The third and final stream presents studies close to our topic, which investigate the macroeconomic determinants of cryptocurrency adoption, offering insights into how economic factors shape the uptake and usage of digital currencies.

Financial inclusion has garnered considerable attention in the scientific community and among policymakers. The significance of financial systems in fostering economic growth is a well-established notion, as diversifying financial channels and instruments is a specific characteristic of advanced economies (Gurley & Shaw, 1955). Extending on this, Aghion et al. (2005) showed that a certain threshold of financial development is crucial for countries to be at the forefront of global technological growth. However, financial inclusion is connected to many socio-economic and cultural factors, including income inequality, literacy, and digital connectivity (Lu et al., 2021; Sarma & Pais, 2011). Besides these, other factors, such as banking costs and branch accessibility, significantly influence the inclusivity of financial services (Allen et al., 2016). Finally, and especially relevant in this digital context, it is found that political instability positively correlates with lower degrees of financial inclusion. At the same time, higher income and education levels relate to higher levels of financial inclusion (Alhassan et al., 2021). Nevertheless, the identified connections are at least bidirectional, as financial inclusion lays the ground for competition and technological investments within financial institutions (Dabla-Norris et al., 2021), making it hard to investigate the causal relationships directly.

Building upon the established financial inclusion narrative, we focus on its role in fulfilling the social aspects of the SDGs. Especially in developing countries, a large proportion of the population does not have a bank account (Demirgüc-Kunt et al., 2022). The transformative power of digital finance in achieving better financial access and, therefore, supporting the SDGs is rooted in the synergy between digital identification systems, simplified banking processes, and interoperable electronic payment systems (Arner et al., 2020). Summing this stream of literature up with some meta-analysis evidence, financial development and inclusion are necessary preconditions for economic prosperity (Bijlsma et al., 2018; Valickova et al., 2015). However, they are complexly connected to a multitude of cofactors.

Turning to the second strand of literature, it can be generally stated that the rise of digital financial services and the growth of mobile and internet use are critical drivers of financial inclusion (Khera et al., 2022; Lenka & Barik, 2018). Even underprivileged groups, such as women entrepreneurs, can benefit from such advancements (Asongu et al., 2024). While digital finance has significantly advanced financial inclusion, it simultaneously introduces a spectrum of risks for households (Yue et al., 2022), encompassing various challenges and requiring a high level of financial literacy (Yang et al., 2023). In this vein, the blockchain, as a very recent technological development, can also be investigated through the lens of financial inclusion. Indeed, it can considerably reduce the cost of financial services (Patel et al., 2022) and enhance the financial access of people with identity issues like poor/refugee populations (Galanti & Özsoy, 2023).

Tokenization can also serve as a tool to resolve conflicts of interest between financial services platforms and their users (Sockin & Xiong, 2023). Therefore, it is unsurprising that countries with higher levels of cryptocurrency, internet usage, and mobile subscriptions generally also show higher levels of financial inclusion and financial sector development (Vincent & Evans, 2019). However, returning to the complexities identified in the first stream of literature, it is also hard to extract causality streams from the visible and researched connections. Contrasting the blockchain-related literature mentioned so far, blockchain can be seen as a two-sided coin since it carries significant financial risks, similar to the more general notion of digital finance. From an economic perspective, the emergence of different non-interoperable blockchains can cause higher transaction costs (Rella, 2019).

Furthermore, more complexity, the necessity for high educational levels, and solid technological equipment could amplify a digital divide within society (Khera et al., 2022). Continuing with the risky aspects of blockchain and crypto adoption comes the market penetration and evolvement of cryptocurrencies. While blockchain's applications in the financial sector need not necessarily be equivalent to cryptocurrencies, these are the currently relevant objects in the context of financial applications. Therefore, it is necessary to keep an eye at least on the most pertinent developments regarding crypto assets pricing, as they are complex and cannot be understood and reflect more than standard supply and demand or fundamental news (Griffin & Shams, 2020). Therefore, the formation of cryptocurrencies' prices is still heavily debated and scientifically investigated. Some models propose fundamental equilibrium pricing (Biais et al., 2023; Kukacka & Kristoufek, 2023). However, a large body of the literature argues for predominantly behavioral factors in crypto assets pricing such as herding (Gemayel & Preda, 2024; Horky et al., 2021; Bouri et al., 2019), sentiment-based evaluation (Horky et al., 2023; Bouteska et al., 2022; Sapkota, 2022) and panic-induced behavior (Su et al., 2023; Vidal-Tomás, 2021). In summary, while blockchain adoption might accelerate financial inclusion – particularly by granting access to a digital means of exchange and speculative assets – it also increases the personal and economic risk given its volatile nature. Finally, as with every technology, there is a potential risk of hacking events with shown effects on the price formation of major cryptocurrencies (Wang et al., 2024).

While the first two streams of literature are necessary for an overall and broad understanding of the topic, the third one is closer to the proposed investigation. Bringing together financial development, financial inclusion, and the crypto realm, it is crucial to understand the determinants of crypto adoption in different contexts. There are several studies making strides in researching the adoption of Bitcoin in particular scenarios, qualitatively by surveying experts or users (Henry et al., 2018), anonymous online marketplaces (Böhme et al., 2015), quantitatively using the small de-anonymized fraction of an online forum (Athey et al., 2017) or within one continent solely (Yermack, 2018). Foley et al. (2022) revealed several key factors influencing Bitcoin usage on a macroeconomic level. Tighter controls on money laundering and stricter capital flow restrictions have been associated with reduced Bitcoin activity, suggesting that regulatory measures can significantly impact cryptocurrency markets.

Conversely, positive GDP growth and higher levels of internet access correlate with increased Bitcoin activity. Cultural factors also play a role, with more individualistic cultures tending to see higher levels of Bitcoin activity. Noteworthy is the notion that Bitcoin adoption is driven by perceived failings of the traditional financial system, such as inflation crises (Saiedi et al., 2021; Cohen, 2017). Furthermore, at least part of the crypto adoption can be attributed to the willingness to speculate (Baur et al., 2018). Besides these factors, the pseudonymity of the crypto space is relevant since a large share of crypto transactions can be attributed to illegal activities such as online narcotics, weapons, and terrorism financing (Böhme et al., 2015; Foley et al., 2019). Similarly, Alhassan et al. (2021) found that higher crypto adoption levels are associated with stricter capital controls in the respective country, hinting at cryptocurrencies' potential use for tax evasion and money laundering.

Finally, switching from the country and personal perspectives to a corporate view, technology readiness, and technology affinity are relevant preconditions for adopting cryptocurrencies (Wong et al., 2020). Saiedi et al. (2021) investigated a broad range of economic determinants of Bitcoin adoption using a panel dataset covering the period from 2014 to 2018. Most importantly, they highlighted the adoption of Bitcoin, which is related to its usefulness as a complement to traditional financial services. Building upon this, we dive deeper by investigating a more recent period and employing a set of additional indices capturing aggregate but broader information. Furthermore, we do not only rely on Bitcoin but also on a much broader notion of general crypto adoption. Nguyen and Nguyen (2024) analyzed 2021 data to examine country-level blockchain adoption, identifying high population and low social connectedness as primary drivers of cryptocurrency adoption, with GDP per capita and inflation playing lesser roles.

Despite extensive research on cryptocurrency adoption, key areas remain underexplored, particularly the effects of development-related aspects such as financial market development, education levels, SDG achievement, and electricity prices. Existing studies have not fully examined how these developmental variables influence cryptocurrency adoption across different countries. Our study addresses this issue and the gaps mentioned in the Introduction by focusing on how related variables impact the adoption of cryptocurrencies.

## 3. Methodological framework

This section provides a comprehensive framework to explore the multifaceted relationship between cryptocurrency adoption and financial inclusion. The empirical strategy uses traditional econometric techniques and advanced ML models for robustness checks.

### *3.1. Empirical model*

In the current study, we aim to develop a comprehensive model (later referred as "Full model") for examining the adoption of cryptocurrency by justifying the need for including key economic variables according to the scholarly literature. The selection criteria for variables in both the base and subsequent models (i.e., Sparse models) follow a literature-based approach with the view of investigating the interlinkages among financial inclusion, the adoption of technologies, and economic impacts. The time scope of the research is, therefore, focused intentionally on recent data, bearing in mind that cryptocurrency markets are going through fast changes.

The base model comprises per capita GDP, Financial Institutions (FI), Financial Markets (FM), inflation rates, and exchange rates, each variable being chosen based on established economic theories linking the latter to technology adoption and financial inclusion promotion. GDP per capita, often used as a proxy for economic development, represents a country's capacity for investment and innovation, specifically in adopting financial technologies such as cryptocurrencies. For example, many studies have investigated the relationship between financial development and economic growth (among others: Bijlsma et al., 2018; Valickova et al., 2015). Additionally, the body of literature on financial inclusion connects economic development to the diffusion of digital financial services, mostly in developing countries where significant portions of the population lack access to traditional banking systems (Demirgüc-Kunt et al., 2022). These findings underline the role of economic growth in promoting the use of cryptocurrencies, hence underlining the importance of GDP per capita as a core variable in the model. Other than economic growth, FI and FM also forge important pathways toward the adoption of FinTech. Included among the determinants of financial inclusion are the cost of banking and branch accessibility (Allen et al., 2016), as well as socio-economic and cultural determinants such as income inequality, literacy level, and digital connectivity (Lu et al., 2021; Sarma & Pais, 2011). These elements, in turn, influence access to financial services and the readiness toward technology (see, inter alia, Wong et al., 2020), determining the ease with which populations can engage in the use of cryptocurrencies. Consequently, FI and FM are core components of the model since they affect the very infrastructural and socio-economic conditions needed for cryptocurrency usage.

Inflation is a key variable in the model, as, historically, periods of high inflation have led to higher demand for alternative assets like cryptocurrency, which can act as a hedge against currency devaluation. This relationship is corroborated by Saiedi et al. (2021), who note that investors tend to take refuge in digital assets during periods of inflation as a means of protection from the erosion in value of fiat money. The inclusion of inflation in the model captures this economic behavior, showing how adverse macroeconomic conditions could trigger using cryptocurrencies as a store-of-value asset. Another important factor influencing cryptocurrency adoption is exchange rate fluctuation, which impacts the cost and attractiveness of cross-border payments and speculative investments. The exchange rate volatility often prompts investors to look for alternative currencies when there is macroeconomic instability. Cohen (2017) points out the relationship between these factors, noting that the adoption of cryptocurrency is usually driven by perceived shortcomings of the traditional financial system. The introduction of the exchange rate volatility, therefore, into the modeling allows for a deeper understanding of how macroeconomic instability could spur the use of digital currencies. Taken together, these factors form a comprehensive framework for understanding cryptocurrency adoption, which is grounded in established economic theories and supported by empirical evidence from the literature.

The baseline model is specified as follows:

$$\begin{aligned} \textit{Cryptocurrency Adoption} = &\beta_0 + \beta_1 \log(GDP_{i,t}) + \beta_2 FI_{i,t} + \beta_3 FM_{i,t} \\ &+ \beta_4 \textit{Inflation}_{i,t} + \beta_5 \textit{Exchange Rate}_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where the subscripts $i$ identify the respective country and $t$ the time dimension, capturing the panel structure of the data. Subsequent models progressively include additional control variables to assess their incremental explanatory power, each selected based on theoretical justification and its potential to interact with core economic variables.

The inclusion of Corporate Tax in Model 2 reflects its impact on the corporate environment and how well cryptocurrencies can be placed as alternatives to the traditional financial system. Higher corporate tax rates could stimulate the desire of companies to adopt cryptocurrencies in order to avoid the heavier burden of taxation. Alhassan et al., 2021 found a positive association between higher levels of cryptocurrency adoption and tighter capital controls, which may suggest that corporate taxation could also affect adoption through similar channels. Model 3 includes the variable of Education as an important determinant of digital literacy, often linked to the capacity for adopting complex technologies such as cryptocurrencies. Higher education levels are associated with increased financial inclusion and use of digital platforms, thus rendering it a crucial determinant in cryptocurrency adoption. Lenka and Barik (2018) observe that digitally literate individuals with higher educational qualifications have a better possibility of using digital financial services, while Alhassan et al. (2021) found that increased income and education levels facilitate greater financial inclusion, which may, in turn, foster the adoption of cryptocurrency. We add Electricity Price to Model 4, which is especially important for cryptocurrency mining given that the process basically is energy-consuming. It means that mining profitability is elastic regarding the cost of electricity, which turns this variable very important to countries that develop large-scale mining operations. Hayes (2017) highlights the heavy effect of electricity costs on the profitability of mining, while low prices attract miners to operate with maximum profit returns.

Additionally, Model 5 introduces Internet Use as a direct driver of cryptocurrency use. Greater access to the internet widens participation in digital financial ecosystems, particularly in regions with low levels of traditional banking facilities. High levels of internet connectivity show a strong correlation with increased use of digital finance (Lenka & Barik, 2018). Demirgüc-Kunt et al. (2022) further highlight that digital finance serves as a substitute for traditional banking systems in the most disadvantaged regions. In Model 6, adding the SDGs Index attempts to grab a wider social and economic environment that determines cryptocurrency adoption. The ability of digital finance to effect meaningful change in achieving the SDGs is firmly tied to increased access to finance. In the view of Arner et al. (2020), digital finance plays a role that is central to attaining goals of financial access, which in turn can strengthen the general objectives of the SDGs. However, in our analysis, the SDGs Index serves as an additional, broad technical control capturing a wide spectrum of development achievements. Economic Freedom is added to Model 7 as a proxy for regulatory frameworks and the ease of doing business. An increase in economic freedom reduces the barriers to financial innovations, thus fostering the use of cryptocurrencies. Wong et al. (2020) state that readiness for technology and a tendency to use digital innovations are highly imperative conditions for the acceptance of cryptocurrencies; hence, enabling economic environments foster increased adoption.

Finally, Model 8 adds the Fragile State Index (FSI) to capture the influence of political and economic instability on the adoption of cryptocurrency. Alhassan et al. (2021) found an association with political instability and reduced financial inclusion, which would hint at a more complicated interaction where instability may limit access to traditional financial services while at the same time increasing interest in cryptocurrencies as alternative financial instruments. This progressive inclusion of variables allows the analyst to systematically assess an extra explanatory contribution of each factor, ensuring that we net out the effect of each determinant on the adoption of cryptocurrency.

The final Full model includes only those variables that show significance across multiple specifications, ensuring a parsimonious and robust analysis:

$$\begin{aligned} \textit{Cryptocurrency Adoption} = &\beta_0 + \beta_1 \log(GDP_{i,t}) + \beta_2 FI_{i,t} + \beta_3 FM_{i,t} \\ &+ \beta_4 \textit{Inflation}_{i,t} + \beta_5 \text{Exchange Rate}_{i,t} \\ &+ \beta_6 \textit{Corporate Tax}_{i,t} + \beta_7 \textit{Education}_{i,t} \\ &+ \beta_8 \textit{Electricity Price}_{i,t} + \beta_9 \textit{Internet Use}_{i,t} \\ &+ \beta_{10} \textit{SDGs Index}_{i,t} + \beta_{11} \textit{Economic Freedom} \\ &+ \beta_{12} FSI + \varepsilon_{i,t} \end{aligned}$$

### 3.2. Model evaluation and analysis

The proposed empirical analysis starts with the application of PFGLS, followed by RLS, and then QR. In order to make the results more robust and the prediction more accurate, the paper further combines ML techniques such as Artificial Neural Networks (ANNs), Naïve Bayes (NB), Extreme Gradient Boosting (XGBoost), Bagging using Random Forest (RF), and Support Vector Machines (SVM) into the framework. Such a multi-faceted approach is particularly well-suited to explain the complex and dynamic nature of cryptocurrency markets and their impact on financial inclusion.

Based on this understanding, the benchmarking analytical framework is founded on PFGLS, which is an estimation method meant to address the major pitfalls of heteroscedasticity and cross-sectional dependence in large panel datasets (Wooldridge, 2010). The PFGLS process starts with the first step being an Ordinary Least Squares (OLS) estimation that aggregates the data using an error covariance matrix for Generalized Least Squares (GLS) that is constructed from the residuals. This approach ensures that the error structures for each country are not restrained, hence allowing robustness to intragroup heteroscedasticity and serial correlation. Further, based on data instability and outliers in cryptocurrency adoption, this study has employed RLS to lessen the effect of extreme observations (Huber, 1981). RLS complements PFGLS by adding robustness to it in cases where spikes in adoption rates, due to changes in the market or regulation shifts, would otherwise lead to biased results. This is important to preserve the precision of the model during rapid changes typical for the cryptocurrency market. Finally, QR adds depth to the research by looking into how economic factors influence different parts of the adoption distribution (Koenker & Hallock, 2001). Unlike standard regression models focusing on average effects, QR provides insights into the variation of economic impacts across different quantiles. This is particularly important in the cryptocurrency markets, since the country-specific characteristics might drive diverse adoption patterns ranging from speculative behavior in wealthier nations to necessity-driven adoption in lower-income countries.

We adopted various state-of-the-art ML methods in order to capture complex and nonlinear relationships that may be missed by conventional econometric models. The motivation for switching from the econometric to the ML methodology is the handling of non-linearities and interactions of the data, which are cumbersome with parametric models.

In the context of classification tasks, the "neuralnet" algorithm is implemented for ANNs with the Resilient Propagation (RPROP) method, in particular using the "RPROP+" and "RPROP-" variants, in order to improve convergence by adapting weight updates depending on the sign of the gradient (Riedmiller, 1994; Riedmiller and Braun, 1993). The SAG algorithm has been added for its efficiency in dealing with large-scale classification problems (Le Roux et al., 2013). In addition to the ANN, we also implement the NB classifier, which is known for simplicity and its effectiveness in handling classification processes (Kibriya et al., 2004; Rennie, Shih, Teevan, & Karger, 2003; Rish, 2001; McCallum & Nigam, 1998). This feature makes it especially beneficial when classifying cryptocurrency adopters over their demographic and economic profiles.

In regression tasks, we adopt both Bagging and Boosting methods, which have been proven to be good at handling continuous explanatory variables like adoption rates. More precisely, the Bagging framework, is applied because it can decrease variance by fitting numerous models on bootstrapped data subsets and thus aggregating their predictions (Breiman, 1996). This especially finds utility in the volatile setting of crypto-currency markets, in which individual model-based predictions might be very unstable. RF, through Bagging, really enhances the accuracy of models and predictions by averaging them out over a large number of decision trees. On the other hand, Boosting enhances the accuracy of the model by concentrating on the misclassified data points from previous models. To achieve this, we employ XGBoost, which is recognized for its computational efficiency and exceptional performance in managing extensive and intricate datasets (Chen & Guestrin, 2016). Additionally, SVM techniques are incorporated into the analysis, especially in the context of high-dimensional datasets, to identify potential non-linear relationships. SVM develops an optimal hyperplane to distinguish classes or predict values, which is suitable for classification and regression tasks related to cryptocurrency adoption (Scholkopf et al., 2000; Cortes & Vapnik, 1995). The application of SVM leads to the efficient representation of the non-linear relationships in financial variables, perhaps stemming from changes in regulations or volatility within the markets.

By shifting from traditional econometric techniques to more complex ML approaches, this wide framework tries to show the complicated, non-linear interrelationships between economic variables and crypto-currency adoption to develop understandings that are more nuanced and refined of the drivers of adoption in different contexts. Viewed together, the mergers of all those different methodologies give a much deeper understanding of the complicated interplays among the economic, technological, and financial determinants underpinning recent cryptocurrency adoption trends.

## 4. Data and descriptive statistics

The empirical examination is constructed upon a dataset that encapsulates a spectrum of economic metrics postulated to influence cryptocurrency adoption. These variables, characterized by diverse measures of financial performance and policy environments, are hypothesized to play integral roles in the adoption patterns of cryptocurrency across different countries.

An overview of all the variables analyzed is shown in Table 1. The variable of interest is *Cryptocurrency Adoption*, which means blockchain adoption ranking index and has been used as a barometer for a country's respective level. Measurement of blockchain adoption has become a very critical point since the block-chain is created pseudonymously and can be used in cross-border applications. To avoid this potential problem, we rely on data collected and supplied by Chainalysis, used in several studies of this type (e.g., Nguyen & Nguyen, 2024; Copestake et al., 2023; Alnasaa et al., 2022). The original index provides an overall ranking and rankings for a number of subcategories. We capture the relevant information by calculating an average over the three most important subcategories: Centralized service value, Retail centralized service value, and P2P exchange trade volume. The result is then normalized between 0 and 100, where 100 represents a full level of crypto adoption, and 0 represents the lowest level.

The first independent variable is consistent with the standard measures of economic output, i.e. *GDP*, reflecting real per capita output in current US dollars. *Education*, is based on formal education through the amount of years of compulsory schooling and is assumed to affect techno-logical adaptability and financial literacy. The *Internet Use* is the proportion of the population that uses the internet and reflects the digital infrastructure of a country and the engagement of its citizens in the use of digital means. *Inflation*, proxied by the GDP deflator, is an indicator of the macroeconomic stability of a country and the faith of the

**Table 1**
Variables' description.

| Abbreviations | Description | Unit of measure | Source |
|---|---|---|---|
| Cryptocurrency Adoption[a] | Cryptocurrency adoption ranking | Normalized Index between 0 (low) and 100 (high) | Chainalysis Global Crypto Adoption Index (2019–2021) |
| GDP | GDP per capita in current USD | Unitary values | World Bank Group |
| Education | Years of compulsory education | Measured in years | World Bank Group |
| Internet Use | % of people using the Internet | Percentage value | World Bank Group |
| Inflation | GDP deflator | Percentage value | World Bank Group |
| Corporate Tax | Corporate tax rate | Percentage value | Tax Foundation |
| Exchange Rate | LCU to USD period average | Unitary values | World Bank Group |
| Economic Freedom | Index of Economic Freedom | Values between 0 (unfree) and 100 (free) | Heritage - index of economic freedom |
| FI | Financial Institutions Index | Values between 0 (low development) and 1 (high development) | International Monetary Fund |
| FM | Financial Markets Index | Values between 0 (low development) and 1 (high development) | International Monetary Fund |
| FSI | Fragile States Index | Values between 0 (very stable state) and 120 (failed state) | Fragile States Index |
| SDGs Index | SDGs Index | Values between 0 (low achievement) and 100 (high achievement) | SDGs Tracker |
| Electricity Price | Average electricity prices per country | Measured in USD. Values for 2020 and 2019 are reversly calculated using the values for 2021 and inflation rate | World Bank Group |

Sources: Authors' elaborations.
[a] Also referred to as "Crypto Adoption."

people in its monetary system. *Corporate Tax* allows a view into the financial environment and fiscal policies that companies have. Indeed, we consider firms and the private sector to be at the core of driving blockchain applications, hence affecting the overall adoption of cryptocurrencies. The *Economic Freedom Index* concept may also underlie this concept, which measures the level of policies and freedom in conducting business, trade, and financial activities. The *FI* and *FM* indices are, in turn, two of the subindices derived from the overall *Financial Development Index* provided by the IMF, measuring the depth, accessibility, and efficiency of financial institutions and markets, respectively. These indices offer insights into the maturity and accessibility of a nation's financial systems (Svirydzenka, 2016). This aggregate index has been preferred for an overall macroeconomic assessment due to the heterogeneity of agents in both financial institutions and markets. *FSI*, instead, refers to a state's vulnerability to conflict or collapse and hence to the stability of a government. While blockchain adoption often correlates with some distrust in governmental actors, a certain level of stability is deemed required if the progress of such complex technology on a broader scale is to be advanced. The *SDGs Index* measures the progress toward the achievement of the SDGs, hence testifying to a nation's broader developmental agenda. Finally, *Electricity Price* is the average price for electricity consumption per KWh.

Complementing the variable descriptions, Table A1 in the Appendix provides a compact statistical overview of key indicators reflecting the range of economic conditions across countries. *Cryptocurrency Adoption* shows an average at 50.235 and a modest skewness, as expected by the index construction. There is a wide dispersion in the *GDP* per capita reflected by a high standard deviation and positive skew, indicating that most countries fall below the average. *Inflation* is highly skewed and leptokurtic, reflecting a few countries with very high rates of inflation. *Corporate tax* rates are spread out, generally left-skewed. Indicators of stability show a moderate dispersion, such as *FSI*. *FM* and *FI* indicate dispersion, though the latter presents a mild positive skew, suggesting a slight concentration toward lower scores. *Economic Freedom* and *SDGs Index* have a mild positive skew, indicating that there are more countries above average. *Education* and *Internet Use* present less dispersion, though the latter shows a negative skew, which would point to digital divide. Skewness for *Exchange Rate* and *Electricity Price* are very high because of remarkable extreme values in these variables, which indicate enormous heterogeneity in the economic policies being followed. In fact, together, all the above measures indicate that the underlying financial variables are heterogeneous and, therefore, provide a critical background to understand and interpret the results of any econometric analysis based on these variables.

Fig. 1 presents the correlation of the standardized selected variables. The magnitude and type of every circle show the size and color saturation, respectively, where high positive correlations show large and dark blue, while high negative ones show large and bright, deep red. This visualization, therefore, assists in finding multicollinearity and infer economic interplays that involve cryptocurrency uptake. Notably, *Cryptocurrency Adoption* is positively correlated with *FM*, *Education* and *Corporate Tax*. In contrast, *Cryptocurrency Adoption* is inversely related to *GDP* and *Electricity Price*, which may indicate a belief in greater cryptocurrency reliance in countries that face macroeconomic challenges.

## 5. Results and discussion

The empirical findings from the panel econometric analysis are

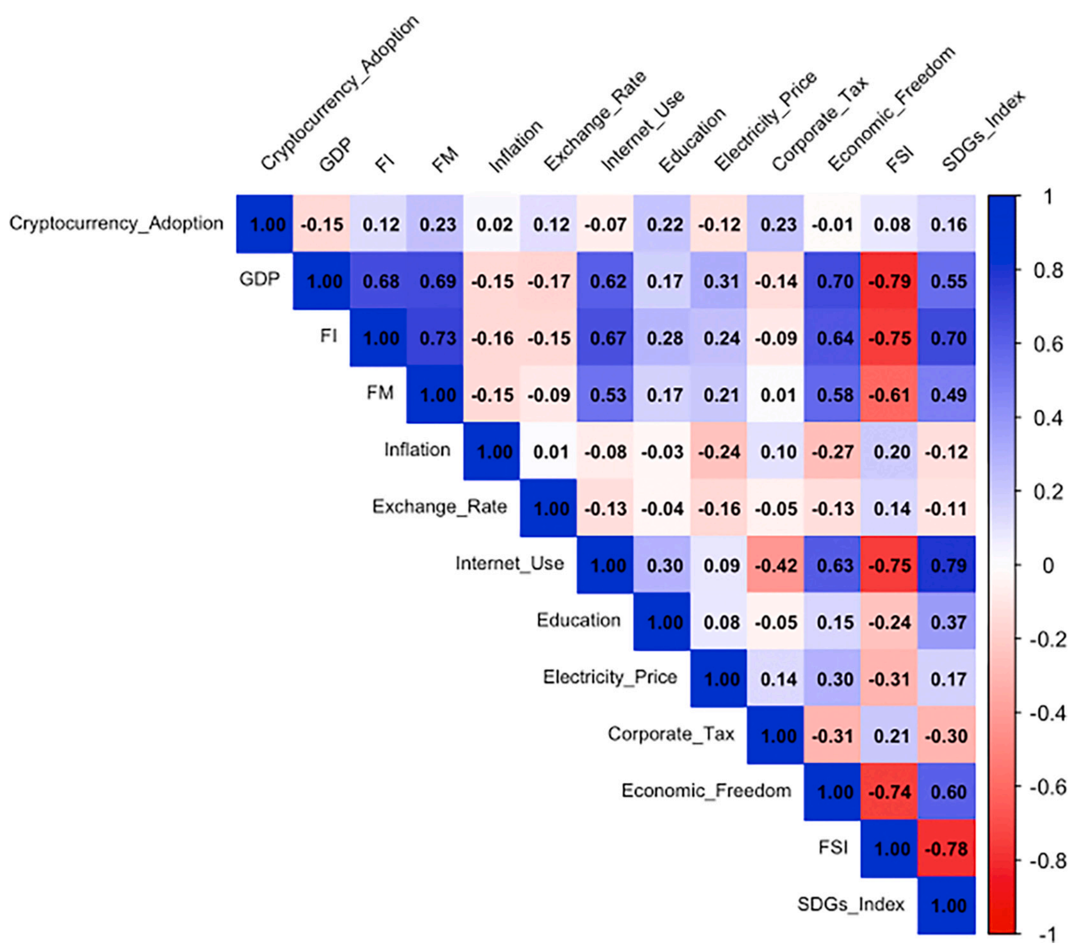


**Fig. 1.** Correlation plot.

**Table 2**
PFGLS estimates.

| | Model Specification | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Sparse |
| GDP | −11.022*** | −10.936*** | −11.588*** | −10.688*** | −13.743*** | −16.696*** | −10.562*** | −10.064*** | −16.880*** |
| | (1.789) | (1.893) | (1.827) | (1.790) | (2.394) | (2.082) | (2.055) | (2.381) | (2.352) |
| FI | 42.658*** | 41.891** | 34.062** | 43.630*** | 38.922** | 20.296 | 41.802** | 44.555** | 11.842 |
| | (12.760) | (12.779) | (12.746) | (12.714) | (13.006) | (13.147) | (13.292) | (13.573) | (12.231) |
| FM | 26.395** | 27.259** | 29.705*** | 26.606** | 28.652*** | 35.729*** | 26.949** | 26.133** | 40.322*** |
| | (8.175) | (8.312) | (7.957) | (8.143) | (8.119) | (7.980) | (8.260) | (8.224) | (7.448) |
| Inflation | −0.0257 | −0.0276 | −0.0381 | −0.0382 | 0.0347 | 0.0401 | 0.0507 | −0.0308 | 0.0142 |
| | (0.054) | (0.054) | (0.054) | (0.054) | (0.063) | (0.061) | (0.063) | (0.054) | (0.062) |
| Exchange Rate | 0.00112 | 0.00111 | 0.000917 | 0.00101 | 0.000949 | 0.000782 | 0.00113 | 0.00113 | 0.0004 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Corporate Tax | | 0.00870 | | | | | | | |
| | | (0.194) | | | | | | | |
| Education | | | 2.1316*** | | | | | | 1.6882** |
| | | | (0.641) | | | | | | (0.584) |
| Electricity Price | | | | −34.844. | | | | | −35.780. |
| | | | | (20.961) | | | | | (19.171) |
| Internet Use | | | | | 0.1705 | | | | −0.0623 |
| | | | | | (0.100) | | | | (0.103) |
| SDGs Index | | | | | | 1.4259*** | | | 1.5259*** |
| | | | | | | (0.268) | | | (0.272) |
| Economic Freedom | | | | | | | −0.0564 | | |
| | | | | | | | (0.239) | | |
| FSI | | | | | | | | 0.0726 | |
| | | | | | | | | (0.128) | |
| Count | 401 | 401 | 384 | 401 | 394 | 394 | 397 | 399 | 375 |
| RMSE | 21.059 | 21.017 | 20.135 | 20.898 | 20.753 | 19.694 | 21.056 | 21.058 | 18.168 |
| Log Likelihood | −2011.22 | −2010.31 | −1980.83 | −2007.72 | −2000.51 | −1976.57 | −2008.85 | −2010.06 | −1928.42 |

Notes: One-way (individual) effects applied through the *pggls* function of the *plm* package in R. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$.

presented across multiple tables, each employing different estimation techniques to discern the impact of various economic indicators on cryptocurrency adoption. A discussion sub-section is later reported.

## 5.1. Results

Table 2 reports the results from PFGLS, which are feasible estimates with individual effects.

The coefficient table, particularly in the final Sparse specification, highlights *GDP*, *FI*, *FM*, *Education*, and *SDGs Index* as significant determinants of *Cryptocurrency Adoption*. An in-depth analysis of the parameters reveals intriguing dynamics. Firstly, the negative coefficient for *GDP* indicates that middle- and low-income countries primarily contribute to *Cryptocurrency Adoption*. While such a finding might initially appear surprising, it is crucial to recognize that these nations often host large cryptocurrency mining operations. Moreover, whereas in developed countries, cryptocurrencies may primarily serve as a new financial asset, in less affluent nations, they play diverse roles, including enabling participation in online transactions. The influence of *FM* on *Cryptocurrency Adoption* suggests that its role as a traded financial asset in capital markets is more pronounced than its adoption through *FI*. The positive impact of *Education* is expected, reflecting the complexity of cryptocurrencies and their infrastructure. *Electricity Price* shows a weakly significant negative effect, likely because higher electricity costs escalate the expenses associated with cryptocurrency adoption, particularly mining. Notably, the *SDGs Index* exhibits a positive sign, though its role as a technical control complicates straightforward interpretation.

These findings align with Alzahrani and Daim (2019), who emphasized the pivotal role of economic and technical determinants in adopting cryptocurrency technologies. Interestingly, *Inflation*, *Exchange Rate*, and *Internet Use* do not significantly influence *Cryptocurrency Adoption*, suggesting that its adoption may not facilitate financial inclusion but is likely driven by an educated elite that employs cryptocurrencies primarily as speculative financial assets, as indicated by the negative *GDP* sign and the prominent role of *FM*.

Table 3 outlines the findings from the RLS regression. The results largely align with those from the PFGLS estimator. The effects of financial markets and electricity prices, seem even more pronounced. Overall, both estimations confirm some overall dynamics. Sign and statistical significance for *GDP*, *FI*, *FM*, *Education*, *Electricity Price*, and *SDGs Index* are confirmed. In addition, *Inflation*, *Corporate Tax*, *Economic Freedom*, and *FSI* variables do not still represent a determinant of crypto adoption.

In Table 4, the results from the QR estimator provide a nuanced view by examining the impact across different quantiles of the cryptocurrency adoption distribution. At the 25th, 50th, and 75th percentiles, the variables of significance consistently show the same patterns as in the previous estimates. Notwithstanding, some interesting deviations occur. First, *FI* is significant only in the Sparse specification at the 25th percentile of crypto adoption, indicating that the presence of financial institutions plays a role in the early stages of cryptocurrency adoption. The most critical deviations occur when comparing the added variables in the complete specification with the PFGLS and RLS results. A significant impact of *Economic Freedom* (Score) and *FSI* is found for QR estimates, but only in the lower quartiles of the crypto adoption distribution. This result emphasizes the distributional effects, reflecting findings by Ogunode et al. (2022), who discussed the role of cryptocurrencies in wealth preservation and inflation hedging amidst distrust in political systems.

Finally, considering the effects of different income groups, we conducted a sample split based on the *GDP* per capita. Specifically, the highest tercile represents high GDP, the lowest tercile represents low GDP, and the middle tercile represents medium GDP. The results are presented in Table 5. This sample split is an essential complement to the previous analysis to gain deeper insights and mainly to shed light on financial inclusion. While the variables of interest stay overall significant, we see substantial differences across the different samples. Starting with the development of financial markets, while the parameter stays positive and significant throughout all samples, the magnitude decreases from low to high GDP. Looking at the GDP itself, we see negative and

**Table 3**
RLS estimates.

| | Model Specification | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Sparse |
| GDP | −11.376*** | −10.246*** | −12.932*** | −11.030*** | −14.286*** | −17.661*** | −11.344*** | −10.114*** | −16.774*** |
| | (1.404) | (1.526) | (1.386) | (1.403) | (2.257) | (1.561) | (1.613) | (1.999) | (2.151) |
| FI | 39.767*** | 37.713*** | 31.682*** | 40.301*** | 34.556** | 11.890 | 37.673*** | 41.396*** | 8.864 |
| | (9.969) | (9.977) | (9.600) | (9.964) | (10.189) | (9.836) | (10.228) | (10.432) | (9.810) |
| FM | 40.645*** | 37.656*** | 44.503*** | 40.911*** | 44.090*** | 49.985*** | 40.354*** | 40.047*** | 51.343*** |
| | (6.261) | (6.415) | (5.979) | (6.247) | (6.489) | (5.972) | (6.302) | (6.323) | (6.014) |
| Inflation | −0.007 | −0.009 | −0.013 | −0.041 | 0.029 | 0.035 | 0.059 | −0.019 | −0.015 |
| | (0.088) | (0.087) | (0.082) | (0.090) | (0.097) | (0.088) | (0.098) | (0.089) | (0.089) |
| Exchange Rate | 0.001* | 0.001* | 0.001 | 0.001* | 0.001 | 0.0004 | 0.0008* | 0.0008* | 0.0002 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Corporate Tax | | 0.315 | | | | | | | |
| | | (0.167) | | | | | | | |
| Education | | | 2.742*** | | | | | | 2.105*** |
| | | | (0.468) | | | | | | (0.457) |
| Electricity Price | | | | −33.031* | | | | | −44.211* |
| | | | | (16.010) | | | | | (15.254) |
| Internet Use | | | | | 0.175* | | | | −0.146 |
| | | | | | (0.098) | | | | (0.101) |
| SDGs Index | | | | | | 1.602*** | | | 1.633*** |
| | | | | | | (0.193) | | | (0.215) |
| Economic Freedom | | | | | | | 0.068 | | |
| | | | | | | | (0.194) | | |
| FSI | | | | | | | | 0.092 | |
| | | | | | | | | (0.109) | |
| Count | 401 | 401 | 384 | 401 | 394 | 394 | 397 | 399 | 375 |
| RMSE | 20.767 | 20.674 | 19.847 | 20.620 | 20.420 | 19.415 | 20.789 | 20.788 | 17.901 |
| Log Likelihood | −2058.72 | −2065.75 | −2039.98 | −2065.56 | −2063.60 | −2033.55 | −2060.49 | −2075.40 | −1977.06 |

Notes: Method: M-estimation. Weighting method: Inverse of the variance. Initialization method: LS; Huber Standard Error. The rlm function via the MASS package in R is used. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$.

**Table 4**
QR estimates.

| | Model Specification | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Sparse | | | Full | | | | |
| | τ = 0.25 | τ = 0.5 | τ = 0.75 | τ = 1 | τ = 0.25 | τ = 0.5 | τ = 0.75 | τ = 1 |
| GDP | −18.104*** | −18.209*** | −18.048*** | −7.574 | −12.513*** | −10.757 ** | −15.216*** | −4.981 |
| | (2.882) | (2.733) | (3.275) | (8.312) | (3.866) | (4.108) | (4.325) | (7.565) |
| FI | 30.441 * | 9.061 | −3.533 | −20.521 | 8.909 | 18.918 | −1.603 | −15.024 |
| | (13.378) | (12.909) | (10.184) | (35.630) | (14.658) | (15.617) | (12.429) | (27.730) |
| FM | 53.038*** | 51.176*** | 52.922*** | 54.400** | 52.182*** | 33.532*** | 43.122*** | 49.163** |
| | (7.357) | (6.931) | (7.061) | (26.594) | (7.604) | (8.852) | (7.711) | (20.670) |
| Inflation | −0.064 | −0.055 | 0.056 | 1.074 | −0.085 | −0.049 | 0.149 | 1.214 |
| | (0.106) | (0.145) | (0.206) | (1.656) | (0.140) | (0.117) | (0.219) | (1.132) |
| Exchange Rate | −0.001 | 0.000 | 0.000 | −0.000 | 0.001 | 0.000 | 0.001 | 0.000 |
| | (0.001) | (0.0008) | (0.0006) | (4.049) | (0.001) | (0.0005) | (0.0006) | (1.942) |
| Internet Use | −0.111 | −0.205 | −0.124 | −0.000 | −0.063 | −0.137 | −0.072 | −0.105 |
| | (0.141) | (0.137) | (0.141) | (0.601) | (0.154) | (0.145) | (0.144) | (0.507) |
| Education | 1.718 ** | 2.334 *** | 2.089 *** | 3.465 | 1.342 * | 1.839 ** | 2.003 ** | 1.605 |
| | (0.631) | (0.706) | (0.496) | (3.464) | (0.715) | (0.663) | (0.669) | (2.176) |
| Electricity Price | −29.933 * | −68.507*** | −59.371*** | −103.777* | −43.433** | −64.190*** | −51.239 | −86.403** |
| | (14.082) | (17.538) | (19.910) | (56.215) | (15.802) | (16.374) | (27.271) | (38.274) |
| Corporate Tax | | | | | 0.785 ** | 0.805 ** | 0.581 ** | −0.065 |
| | | | | | (0.288) | (0.307) | (0.238) | (0.851) |
| Economic Freedom | | | | | 0.728 * | 0.650 ** | 0.332 | 0.104 |
| | | | | | (0.328) | (0.250) | (0.227) | (0.733) |
| FSI | | | | | 0.487 ** | 0.484 ** | 0.185 | 0.341 |
| | | | | | (0.191) | (0.182) | (0.159) | (0.350) |
| SDGs Index | 1.222 *** | 1.978 *** | 1.785 *** | 0.206 | 1.858 *** | 1.850 *** | 1.773 *** | 0.883 |
| | (0.267) | (0.357) | (0.326) | (1.310) | (0.341) | (0.287) | (0.338) | (0.794) |
| Count | 375 | 375 | 375 | 375 | 375 | 375 | 375 | 375 |
| RMSE | 22.445 | 18.202 | 22.757 | 43.728 | 22.009 | 17.480 | 21.603 | 42.696 |
| R-squared | 0.429 | 0.407 | 0.382 | 0.404 | 0.449 | 0.432 | 0.398 | 0.426 |

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$. Weight: Inverse Standard Deviation. Bootstrapped Standard Errors and Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall-Sheather. Quantile method: Rankit (Cleveland). A Pseudo $R^2$ is calculated following Koenker and Machado (1999).

**Table 5**
Sample split by GDP.

| | Model Specification | | | | | |
|---|---|---|---|---|---|---|
| | Sparse – high GDP | Full – high GDP | Sparse – med. GDP | Full – med. GDP | Sparse – low GDP | Full – low GDP |
| GDP | −21.532*** | −28.019*** | −15.132*** | −5.638 | 0.570 | −3.700 |
| | (4.229) | (4.559) | (4.111) | (5.356) | (5.138) | (5.521) |
| FI | 37.415 *** | 24.735 * | 23.129 | 27.469 . | −30.402 . (17.176) | −18.333 |
| | (10.741) | (11.890) | (14.050) | (14.376) | | (18.778) |
| FM | 36.076 *** | 43.495 *** | 50.762 *** | 37.856 *** | 82.017 *** | 77.815 *** |
| | (6.215) | (5.991) | (7.663) | (8.363) | (13.925) | (15.979) |
| Inflation | 0.166 | 0.040 | 0.169 | 0.190 | −0.055 | −0.106 |
| | (0.254) | (0.234) | (0.113) | (0.119) | (0.100) | (0.110) |
| Exchange Rate | −0.102 ** | −0.089 ** | −0.002 | −0.001 | 0.000 | 0.000 |
| | (0.033) | (0.031) | (0.001) | (0.001) | (0.000) | (0.000) |
| Internet Use | −0.512 . | −0.690 ** | 0.027 | −0.074 | −0.273 . | −0.141 |
| | (0.266) | (0.247) | (0.180) | (0.180) | (0.144) | (0.153) |
| Education | −0.987 | −0.140 | 3.309 *** | 2.964 *** | 1.553 . | 1.831 * |
| | (0.752) | (0.757) | (0.512) | (0.510) | (0.838) | (0.834) |
| Electricity Price | −15.621 | −31.978 . | −35.977 | −24.069 | −38.602 . | −46.246 . |
| | (20.825) | (19.348) | (23.743) | (23.269) | (23.396) | (25.940) |
| Corporate Tax | | 0.131 | | 0.521 ** | | 0.758 |
| | | (0.233) | | (0.203) | | (0.470) |
| Economic Freedom | | 1.164 *** | | 0.371 | | −0.109 |
| | | (0.245) | | (0.258) | | (0.363) |
| FSI | | 0.114 | | 0.420 * | | 0.363 . |
| | | (0.126) | | (0.173) | | (0.221) |
| SDGs Index | 1.303 *** | 1.327 *** | 1.571 *** | 1.917 *** | 1.128 ** | 1.528 ** |
| | (0.249) | (0.281) | (0.349) | (0.365) | (0.433) | (0.480) |
| Count | 116 | 116 | 132 | 132 | 127 | 127 |
| RMSE | 13.195 | 16.976 | 19.263 | 12.006 | 16.142 | 18.766 |
| R-squared | 0.6254 | 0.68754 | 0.50579 | 0.54704 | 0.33677 | 0.37173 |
| Log Likelihood | −1514.15 | −1658.83 | −1707.75 | −1471.01 | −1635.81 | −1695.81 |

Notes: One-way (individual) effects applied through the *pggls* function of the *plm* package in R. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$.

significant parameters only in the richer and medium countries, while in low countries, the parameter even turns positive in one specification. This might indicate a maximum crypto adoption in medium-income countries with already a certain level of development. The effect of education vanishes in more affluent countries; however, the exchange rate gains importance in these countries, yielding the role of cryptocurrencies as a secure asset. Finally, while *Economic Freedom* is significant in richer countries, the more relevant precondition is a stable environment, as indicated by substantial and positive parameters of *FSI*.

### 5.2. Discussion

The empirical findings from the econometric analysis, underpinned by PFGLS, RLS, and QR estimates, highlight how economic indicators influence cryptocurrency adoption. This narrative is supported and enriched by a diverse range of studies in the literature, which offer insights into the multifaceted relationship between economic factors and the uptake of digital currencies and technologies. Recalling the introductory idea of a potential connection between financial inclusion and crypto adoption, the results leave space for interpretation and cautious pessimism. Although, at least in lower quantiles of the crypto adoption and for poorer countries, *Economic Freedom* and political stability play a role, which implies a potential action that cryptos can play in financial inclusion, most of our results yield in another direction. It seems that crypto adoption is mainly driven by an educated elite seeking more speculative investment alternatives, which aligns with the notion that cryptocurrencies mainly fulfill the need for speculative alternative investment opportunities (Baur et al., 2018). The more substantial magnitude of financial market development in poorer countries also indicates that financial markets, usually more accessed by richer and already financially included people (Das & Mohapatra, 2003), play a primary role in crypto adoption. However, this somewhat contradicts crypto adoption's contribution to financial inclusion. Especially as the development of financial institutions is not relevant in these countries, it is interesting to note that in most specifications, neither exchange rate nor inflation seems to affect crypto adoption. This contradicts the findings reported by Saiedi et al. (2021) and Cohen (2017) but is in line with Nguyen and Nguyen (2024). One interpretation could be that the actual use of cryptocurrencies as currencies, i.e., alternatives in case of volatile exchange rates and high inflation, is quite limited. However, one must consider the specific period around the COVID-19 pandemic. Future research should investigate this finding further, as the primary uses of cryptocurrencies ultimately determine the optimal policy reactions. The significance of electricity prices is as expected, as mining activities are energy intensive, and therefore, the return ratios of mining are highly dependent on energy supply and prices. Finally, it is notable that internet use is not relevant to crypto adoption. We assume that overall, the share of crypto users is much lower than that of internet users. Therefore, the fundamental development of the internet does not play a crucial role.

## 6. Robustness checks

The robustness of panel data findings is further substantiated by applying several ML algorithms.

Table 6 presents the results from ML classification models[1] employing different configurations of ANN algorithms, specifically RPROP+, RPROP-, and SAG. The classification outcomes are reported for both Sparse (with independent variables *GDP*, *FI*, *FM*, *Education*, *Internet Use*, *Inflation*, *Exchange Rate*, *SDGs Index* and *Electricity Price*), and Full model specifications across six metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE),

[1] For all classification models presented in this analysis, the target variable, 'cryptocurrency adoption,' has been converted into a binary format. This dichotomization was achieved by assigning a value of 1 to observations falling above the 90th percentile of the original 'cryptocurrency adoption' variable, and a value of 0 to all other observations.

**Table 6**
ML classification models results.

| Statistics | Algorithm/Model | | | | | |
|---|---|---|---|---|---|---|
| | Neural Network (RPROP+) | | Neural Network (RPROP-) | | Neural Network (SAG) | |
| | Sparse | Full | Sparse | Full | Sparse | Full |
| Mean Squared Error | 0.122 | 0.111 | 0.123 | 0.105 | 0.129 | 0.108 |
| Root Mean Squared Error | 0.350 | 0.333 | 0.350 | 0.323 | 0.360 | 0.328 |
| Mean Absolute Error | 0.191 | 0.178 | 0.191 | 0.164 | 0.193 | 0.149 |
| R-squared | 0.955 | 0.701 | 0.954 | 0.671 | 0.905 | 0.586 |
| Accuracy | 0.866 | 0.866 | 0.866 | 0.866 | 0.857 | 0.839 |
| ROC-AUC | 0.620 | 0.727 | 0.578 | 0.745 | 0.468 | 0.713 |

Notes: The *neuralnet* function in R is applied using three neural layers with 2, 1 and 1 neuron each. Activation function: *softplus*.

R-squared, Accuracy, and ROC-AUC. For the classification models reported, the binary version of the cryptocurrency adoption was created through the 90th quantile threshold.

The reported metrics provide insight into model performance. For instance, MSE, RMSE, and MAE show that all models report relatively low error rates, where Full models generally have slightly better performance than Sparse models. This suggests that with an expanded set of variables, models increase in predictive accuracy. R-squared values, representing the proportion of variance explained by the model, vary considerably for different algorithms and model specification. The highest value was achieved by RPROP+ algorithm for the considered Sparse model: 0.955, while the lowest R-squared has been achieved by the SAG algorithm for the Full model: 0.586. This variation underlines the impact of algorithm's choice and model's complexity on predictive performance.

In addition, more information could be obtained from the Accuracy and ROC-AUC scores with regard to the classification capability of the models. The accuracy values remain constantly high throughout all models, ranging from 0.84 to 0.87, thus showing good robustness in class prediction. However, the ROC-AUC statistic – a measure of model performance based on its discrimination capability between classes effectively – varies quite a lot, from a high of 0.745 in the RPROP- algorithm for the Full model to a low of 0.468 for the SAG algorithm under the Sparse model. These differences make this trade-off between the model's complexity and efficacy within classification clear.

Fig. 2 shows the structure of an ANN with the RPROP+ algorithm for a Sparse model configuration. Fig. A1 in the Appendix shows the results for a Full model configuration. The scheme reveals a set of input variables: *GDP*, *FM*, *FI*, *Education*, *Internet Use*, *Inflation*, *Exchange Rate*, *SDGs Index*, and *Electricity Price*, each denoted as I1 through I9, respectively. These inputs are connected-by weighted paths, represented with lines of different thickness-to hidden layers H1 and H2, assuming a transformation of input data through the network's hidden neurons.

Fig. 2 gives an idea of the structure of the considered ANN model and thus suggests that the most important variables highlighted in the previous panel data analysis, most likely, form the Sparse model. The figure can enable us to conceptualize how all the input features may together provide good prediction for crypto-currency adoption, with each of the input variables contributing differentially based on the unique weights. Fig. 3 below gives a better insight into weights of the model.

Fig. 3 shows the importance scores, quantified by Olden's method, which give a measure of the relative influence that each variable has on the classification decision of the model. The variable *Education* is presenting the highest positive score, followed by *FM*, which might imply a strong influence in the prediction of cryptocurrency adoption. *FM* also shows a positive score, indicating its predictive power within the model. The *SDG Index* and *Inflation* are relevant to a fair extent, with a positive contribution toward the model, whereas lower positive importance is contributed by *Exchange Rate* and *GDP*.

The distribution of the importance scores shows complex interactions of each predictor and varying degrees of influence within the ANN model. Being *Education* the most influential predictor, it may indicate that a higher level of compulsory education strongly correlates with C*ryptocurrency Adoption* and perhaps reflects the role of education in understanding and utilizing cryptography technologies. The negative weight for *FI* likely reflects that more robust financial institutions could be inversely related to the propensity to adopt cryptocurrencies, perhaps due to better access to traditional financial services. Importantly, these importance scores should be interpreted cautiously, because they reflect the internal modeling dynamics of the ANN and are not direct causal inferences.

Results of the performance measures for the NB classification models are shown in Table 7; both Sparse and Full model specifications are reported.

Whereas the Accuracy of the Sparse model stands at 0.839, that for the Full model is 0.821. This again confirms the classification ANN result that the sparse model, which makes use of the reduced set of predictors, may, in fact correctly classify instances much better than with the Full model, which makes use of a much more extensive array of variables. The sensitivity or true positive rate is quite high at 0.969 for the Sparse model, but it drops to 0.897 for the Full model. This would tend to indicate that the Sparse model is somewhat better at correctly assigning cases of *Cryptocurrency Adoption*. Both models have poor ROC-AUC scores below 0.7, which stands for fair though not excellent capability in model discrimination between the positive and negative classes. Whereas the Full model's ROC-AUC is higher than that of the Sparse model, this indeed can hint at such an additional variable contributing to the model's discrimination capability despite worse overall accuracy.

This moves the analysis from the classification models of ML to the regression models, enabling a more granular analysis of the continuous variables impacting crypto currency adoption. Table 8 presents results of the ML regression algorithms Neural Network (*nnet*), Boosting, Bagging and SVM in both their Sparse and Full model versions.

The results of the regression models, using ANN, Boosting, Bagging, and SVM algorithms for Sparse and Full models, are shown in Table 8. On the whole, the Full models perform better than the Sparse ones, and among these, the best fit results from the Full-SVM model, as shown by the lowest MSE of 0.356, RMSE of 0.597, and MAE of 0.435. Among the models presented, the ANN Sparse model has the highest R-squared value of 0.830, thus showing the model supports a high percentage variance of the dependent variable. However, this does not essentially mean better predictive performance.

Fig. 4 presents the graphs of variable importance from two different ML models, namely the XGBoost and Bagging RF models.

The left graph shows the feature importance derived from the XGBoost algorithm. *FM* is ranked first by its importance ranking, with the highest score, which might indicate that *FM* is going to be the most predictive of cryptocurrency adoption in this model. The right graph illustrates the importance of the variables in the RF algorithm. The dotted lines represent the distribution of the importance score across several trees within the forest. The dot represents the average of those. Again, *FM* is the most important variable, similar in standing to that in the XGBoost Model.

Fig. 5 presents a heat map of weights from an ANN model through the *nnet* regression for both Sparse and Full model specifications. The Sparse model heat map shows that the weights are further apart, especially for the *FM* and *Education* variables. Both have quite significant positive weights to influence the first neuron, ensuring the importance of both in the model. However, even though the whole model heat map includes more variables, it shows similarly that *Education* bears a notable positive weight across both neurons, ensuring its significant role in predicting cryptocurrency adoption in line with previous models. Whereas other features such as *GDP*, *FSI*, and *Corporate Tax* have different weights between the neurons, this may indicate a more complicated pattern internal to the data, captured nonlinearly by the

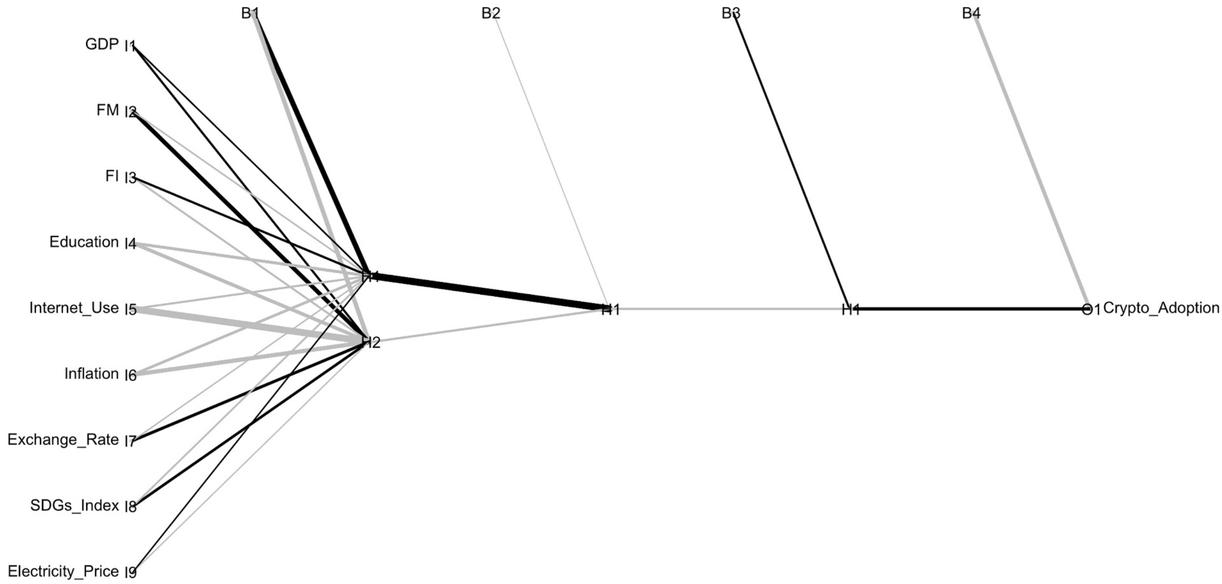


**Fig. 2.** Classification ANN (RPROP+), Sparse model.

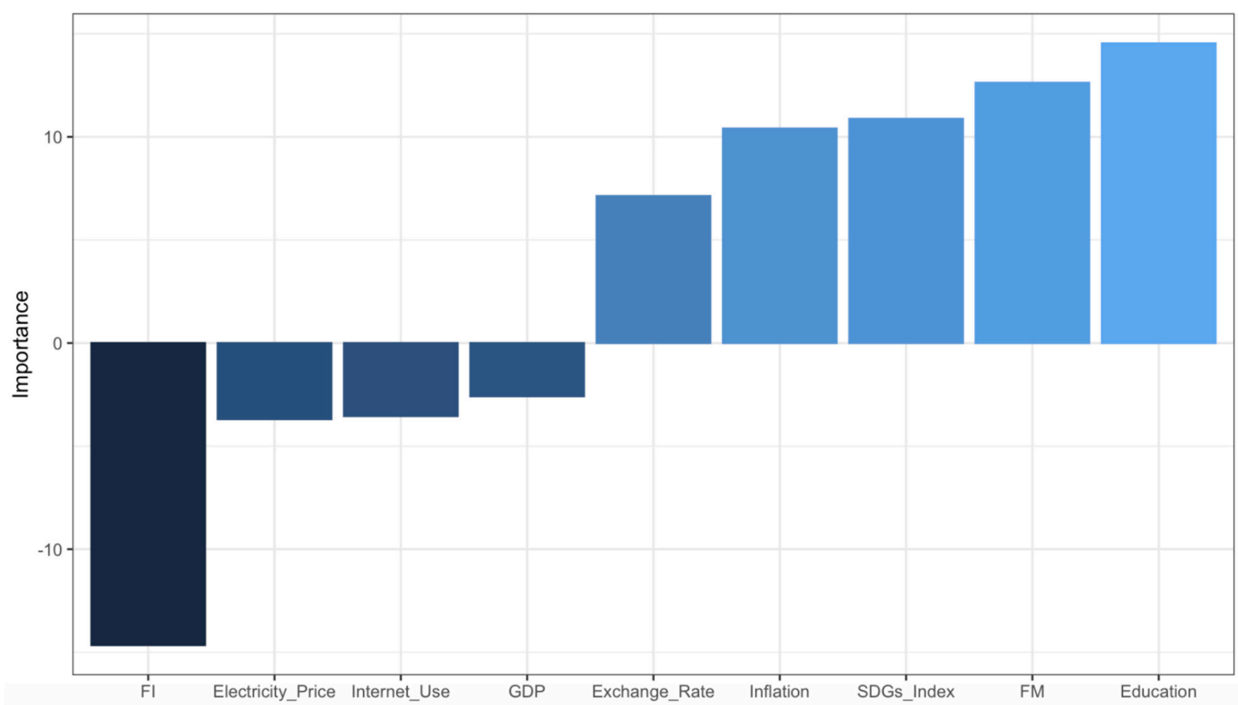


**Fig. 3.** Importance Score Classification test, ANN (RPROP+), Sparse model.

**Table 7**
NB model results.

| Statistics | Sparse | Full |
|---|---|---|
| Accuracy | 0.839 | 0.821 |
| Sensitivity | 0.969 | 0.897 |
| Specificity | 0.000 | 0.333 |
| ROC-AUC | 0.485 | 0.615 |
| Count | 375 | 375 |

network. Conversely, *Inflation*, for instance, has a quite strong negative weight in neuron 2 in the Full model, which shows that it stands in reverse relation to the target variable in this particular ANN configuration, in clear contrast to the effect observed in the Sparse model.

The fact that *Education* is consistently visible across both Sparse and Full models in Fig. 5 underlines its critical influence within the ANN framework. That is to say, though it was less important in previous ML models, *Education* then becomes a very strong predictor when combined with interactions from other variables in the context of ANN regression. This points out that predictive modeling is often multifaceted, and sometimes the relevance of predictors can change significantly across different types and configurations of models.

A study in such a realm of investigation goes on to examine, through various ML models, the complex dynamics involved in the adoption of cryptocurrencies; each brings out unique variable interactions and

**Table 8**
ML regression model results.

| | Algorithm/Model | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Neural Network (*nnet*) | | Boosting | | Bagging (RF) | | SVM | |
| | Sparse | Full | Sparse | Full | Sparse | Full | Sparse | Full |
| Mean Squared Error | 0.873 | 0.839 | 0.393 | 0.387 | 0.422 | 0.394 | 0.385 | 0.356 |
| Root Mean Squared Error | 0.935 | 0.916 | 0.627 | 0.622 | 0.650 | 0.628 | 0.620 | 0.597 |
| Mean Absolute Error | 0.744 | 0.698 | 0.484 | 0.477 | 0.504 | 0.493 | 0.453 | 0.435 |
| R-squared | 0.830 | 0.724 | 0.619 | 0.624 | 0.604 | 0.635 | 0.629 | 0.656 |

Notes: All models are run in R. Specifically, we apply the *nnet* function for a neural network for regression with three neural layers containing 2, 1, and 1 neuron each. We use the *xgboost* function for the boosting model with cross-validated boosting rounds, the *randomForest* function for the bagging procedure with the number of trees set to 100, and the *ksvm* function for the SVM framework with the kernel set to *rbfdot* and C equal to 4.5.

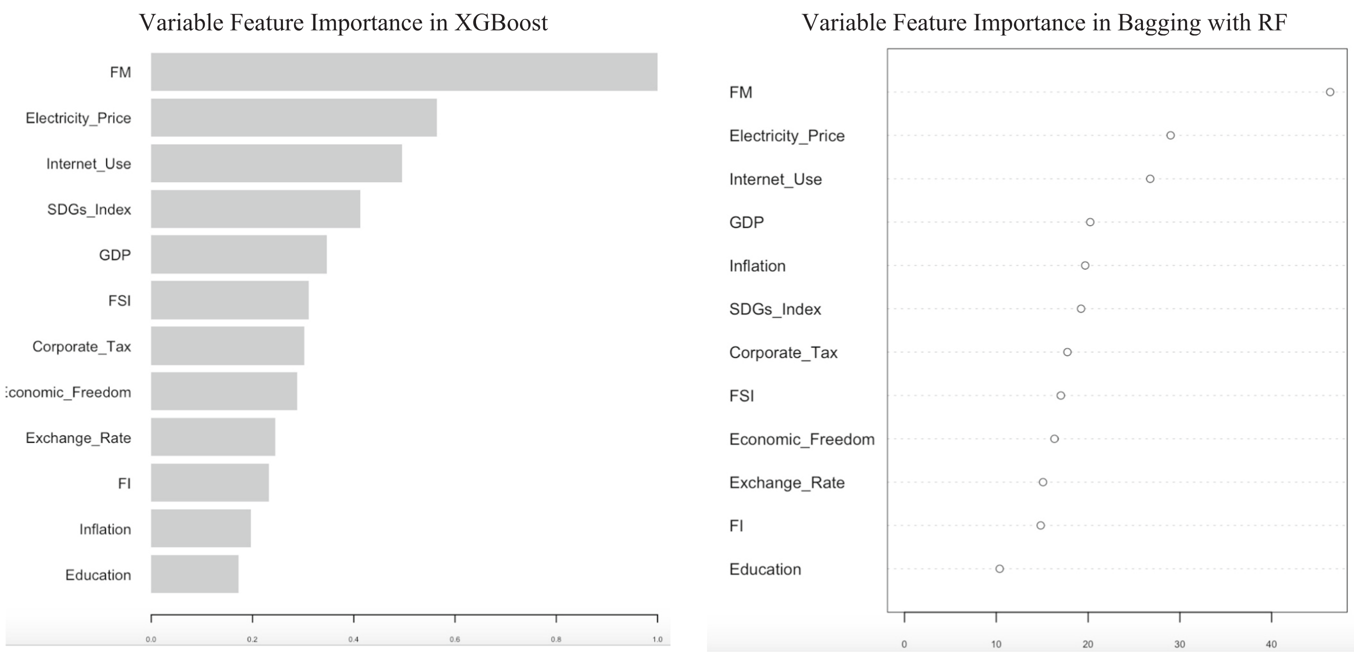


**Fig. 4.** Boosting vs. Bagging regression results, Full model.

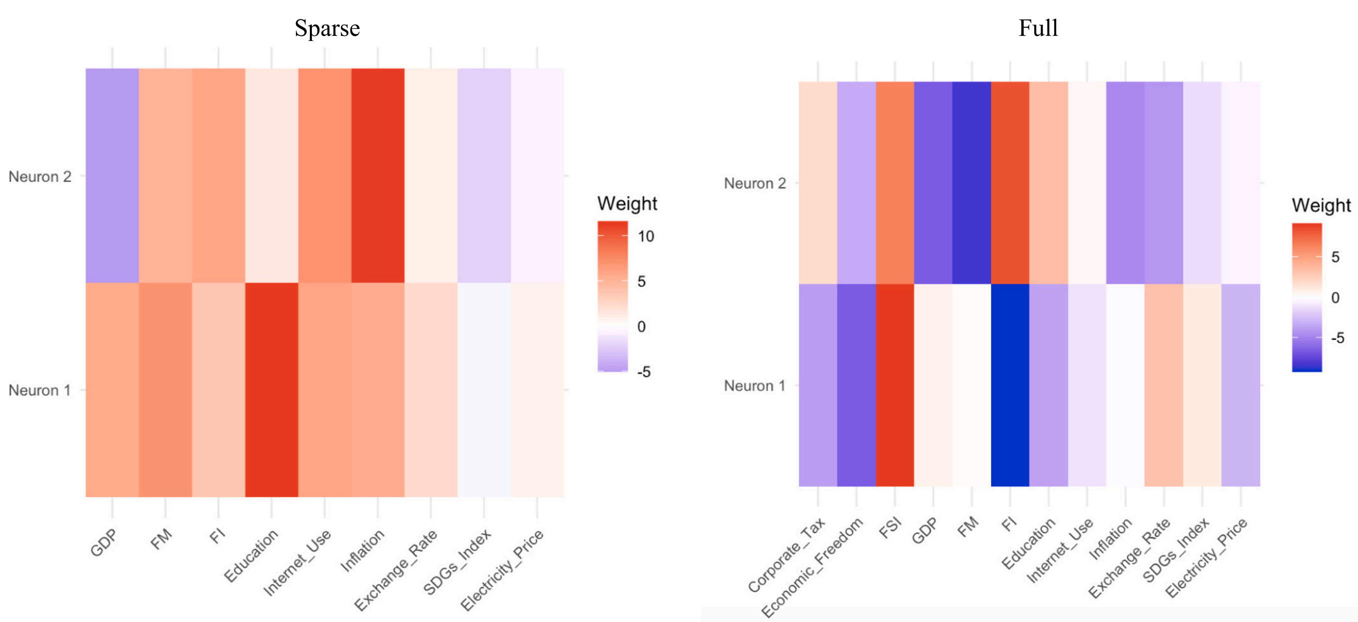


**Fig. 5.** ANN (*nnet*) input layer weights to neurons model results.

outcomes shaped by differing assumptions and optimization methods. These are not conflicting views but altogether enhance the understanding of what drives interests in cryptocurrency-thus providing critical insight into this evolving landscape.

Another striking trend in the models is the differential reliance on certain predictors. For instance, FM variables feature rather prominently on aspects such as XGBoost and Bagging with RF, which postulate that the functioning of financial markets contributes to the increased adoption of the cryptocurrencies. This is in conjunction with prior findings by Das & Mohapatra, 2003, where financial market reforms have conventionally favored economic growth and capital flow, with relative success across different income levels. The attention toward FM indicators reflects that persons with experience in traditional finance are generally more willing to learn about cryptocurrency, either for investment reasons or as an alternative financial instrument.

In contrast to these models, ANN brings to light the educational factors of influence, pointing at digital literacy and the level of education as socioeconomic drivers of cryptocurrency adoption. This indeed goes in tandem with works such as Lenka and Barik (2018), where an increase in the access to education and digitized services has been seen to raise financial inclusion by manifold. Therefore, higher rates of educated individuals can result in increased digital adoption of financial tools and better financial inclusion. For example, studies by Alhassan et al. (2021) show that in regions such as the Middle East and North Africa, education and income are very vital toward financial inclusion, depicting scenarios where a well-educated individual can always find their way around through the new technological innovations. This therefore denotes that there is a strong relationship between education and financial accessibility, suggesting that high levels of education will be much required for easy navigation in innovations that would come along like cryptocurrency.

Therefore, this variation in predictor importance across models, complementing rather than contradicting one another and enriching the analysis. For instance, high influences of FM variables across the different models, such as XGBoost and Bagging, emphasize more general economic conditions, such as available markets and enabling regulations that are needed to make widespread adoption possible. Meanwhile, the emphasis on educational factors in ANN models points to the use of digital literacy as a means for empowering individuals in their efforts to effectively engage with cryptocurrencies. Indeed, this may well apply to low-income regions that have high levels of financial exclusion but where education could be an important lever for financial digital inclusion. In this regard, a more related view is that of Demirgüc-Kunt et al. (2022), who present how mobile money and other digital services have the capacity to increase financial inclusions for the underserved because such options provide them with the means to manage and develop their assets. Also, Aghion et al. (2005) further emphasize this twofold view by considering that countries with a more sophisticated financial system would be in a better position to catch up with modern technology than countries with less-developed financial systems. These ML models, therefore, identify the inclusion of institutional and personal variables as significant in their adoption of cryptocurrencies-a claim that is consistent with widely accepted economic theories.

In conclusion, the variation across models simply reflects that cryptocurrency markets are very diverse, and these conditions, along with individual circumstances, affect the issue of adoption. These robustness checks bolster the empirical findings from the main econometric analysis involving PFGLS, RLS, and QR methods, which underscore the significance of economic and financial development on cryptocurrency adoption.

## 7. Concluding remarks and policy recommendations

This study examines how economic and financial development factors influence cryptocurrency adoption. It builds on previous research related to the SDGs and financial inclusion as drivers of economic growth, drawing insights from studies by Demirgüc-Kunt et al. (2022) and Arner et al. (2020). With further reference to recent studies by Nguyen and Nguyen (2024) and Saiedi et al. (2021), this analysis adds new dimensions to the current understanding of cryptocurrency adoption.

The empirical results indicate that GDP, financial market development, education levels, SDG achievement and electricity prices significantly influence cryptocurrency adoption. These findings align with broader discussions on the role of financial infrastructure in economic development and the impact of technological innovations such as blockchain applications. Notably, the strong and consistent impact of financial market development highlights cryptocurrency's role as a high-risk digital asset in the trading space. Additionally, the link between higher educational levels and increased cryptocurrency use suggests that awareness and understanding play a big part in adoption. Our third major result is the negative role of electricity prices which are potentially connected to respective energy intensive mining activities. Finally, SDG achievement is positively connected to crypto adoption.

From a policy perspective, the relationship between GDP as well as SDG alignment and cryptocurrency adoption presents an opportunity for middle-income countries to leverage cryptocurrencies for economic growth. This should, however, be done in a very measured way, bearing in mind the role of financial markets and education levels, which also might risk deepening the digital divide. To fill this gap, for instance, one desires to see the policymaker initiate a program of promoting financial literacy and other digital skills necessary for cryptocurrencies and blockchain. This may be all the more significant for the developing economies since, as Khera et al. (2022) noted, despite the fact that digital financial services are an important factor in fostering financial inclusion, such progress can be highly heterogeneous across different regions.

Form a methodological point of view, the ML models provide valuable insights that complement traditional econometric methods by their ability to incorporate nonlinear relationships between the predictors of cryptocurrency adoption. Techniques such as neural networks and boosting models highlighted the varying importance of factors like financial markets and education, showing that while traditional methods capture broad trends, ML approaches are more adept at identifying complex patterns. The approach is in agreement with Nguyen & Nguyen, 2024, who identify the interrelatedness of technological, social, economic, cultural, and political factors influencing crypto currency adoption.

Therefore, although cryptocurrencies have great potential for contributing to financial development, especially through their role in speculative investments and technologically advanced environments, their use has to be considered with care. The contribution of this paper to the fast-growing literature is related to the empirical evidence of the economic conditions and factors that drive cryptocurrency adoption and discussion about their implications for financial inclusion. Future research should address current data limitations and extending the temporal scope will allow for a better understanding of the rapidly evolving cryptocurrency landscape and its broader implications for financial inclusion. The findings from both ML and traditional methods suggest that targeted interventions are essential to ensure that cryptocurrencies support, rather than hinder, financial inclusion. In this regard, regulations such as the European MiCA can be considered for future academic assessments. Finally, the impact on financial inclusion in emerging countries is worth a more detailed investigation in future work.

## Acknowledgements

The views expressed in this paper are those of the authors and do not necessarily represent those of the Slovak National Bank, the Eurosystem, or any of the institutions with which the authors are affiliated. All errors and opinions are ours. All standard disclaimers apply.

## Appendix A. Appendix

**Table A1**
Descriptive statistics.

| Variable | Mean | Median | Std. Dev. | Skewness | Kurtosis | Range | IQR |
|---|---|---|---|---|---|---|---|
| Cryptocurrency Adoption | 50.235 | 51.533 | 24.078 | −0.110 | 2.230 | 100.000 | 34.611 |
| Corporate Tax | 22.669 | 25.000 | 7.861 | −0.789 | 3.468 | 37.500 | 10.907 |
| Economic Freedom | 63.283 | 63.000 | 9.681 | −0.184 | 3.675 | 64.500 | 13.300 |
| FSI | 62.801 | 67.400 | 23.522 | −0.267 | 2.269 | 98.900 | 35.150 |
| GDP | 17,939.180 | 7018.222 | 24,572.792 | 2.437 | 10.688 | 182,173.631 | 20,678.264 |
| FM | 0.255 | 0.142 | 0.273 | 0.863 | 2.425 | 0.921 | 0.436 |
| FI | 0.470 | 0.458 | 0.205 | 0.389 | 2.338 | 0.888 | 0.329 |
| Education | 10.017 | 10.000 | 2.445 | −0.106 | 3.129 | 16.000 | 3.000 |
| Internet Use | 68.311 | 75.940 | 24.397 | −0.825 | 2.598 | 93.982 | 34.941 |
| Inflation | 7.717 | 2.839 | 33.610 | 14.037 | 237.238 | 631.242 | 5.116 |
| Exchange Rate | 711.385 | 11.383 | 2644.024 | 6.009 | 44.287 | 23,208.065 | 132.370 |
| SDGs Index | 69.085 | 70.100 | 9.269 | −0.466 | 2.529 | 44.500 | 13.500 |
| Electricity Price | 0.128 | 0.116 | 0.078 | 0.946 | 3.849 | 0.411 | 0.106 |

Notes: Std. Dev.: Standard Deviation; IQR: Inter-Quartile Range.

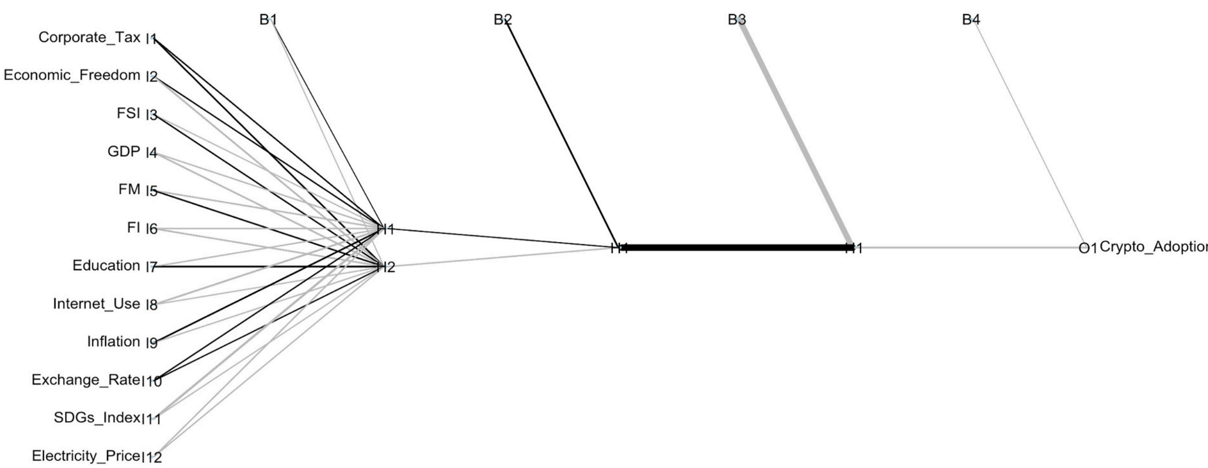


**Fig. A1.** Classification ANN (RPROP+), Full model.

### Data availability

The original data sources are cited within the text. The constructed dataset used for the analysis is available from the corresponding author upon reasonable request.

### References

Aghion, P., Howitt, P., & Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. *The Quarterly Journal of Economics, 120*(1), 173–222.
Ahmad, A. H., Green, C., & Jiang, F. (2020). Mobile money, financial inclusion, and development: A review with reference to African experience. *Journal of Economic Surveys, 34*(4), 753–792.
Alhassan, A., Li, L., Reddy, K., & Duppati, G. (2021). The relationship between political instability and financial inclusion: Evidence from Middle East and North Africa. *International Journal of Finance and Economics, 26*(1), 353–374.
Allen, F., Demirgüc-Kunt, A., Klapper, L., & Peria, M. S. M. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation, 27*, 1–30.
Alnasaa, M., Gueorguiev, N., Honda, J., Imamoglu, E., Mauro, P., Primus, K., & Rozhkov, D. (2022). Crypto-assets, corruption, and capital controls: Cross-country correlations. *Economics Letters, 215*, Article 110492.
Alzahrani, S., & Daim, T. (2019). Evaluation of the cryptocurrency adoption decision using Hierarchical Decision Modeling (HDM). In *2019 Portland International Conference on Management of Engineering and Technology (PICMET)*.
Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Veidt, R. (2020). Sustainability, FinTech and financial inclusion. *European Business Organization Law Review, 21*, 7–35.
Asongu, S. A., Agyemang-Mintah, P., Nnanna, J., & Ngoungou, Y. E. (2024). Mobile money innovations, income inequality and gender inclusion in sub-Saharan Africa. *Financial Innovation, 10*(11).
Athey, S., Catalini, C., & Tucker, C. (2017). *The digital privacy paradox: Small money, small costs, small talk* (Vol. No. w23488). National Bureau of Economic Research.
Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets Institutions and Money, 54*, 177–189.
Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., & Menkveld, A. J. (2023). Equilibrium bitcoin pricing. *The Journal of Finance, 78*(2), 967–1014.
Bijlsma, M., Kool, C., & Non, M. (2018). The effect of financial development on economic growth: A meta-analysis. *Applied Economics, 50*(57), 6128–6148.
Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives, 29*(2), 213–238.
Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters, 29*, 216–221.
Bouteska, A., Mefteh-Wali, S., & Dang, T. (2022). Predictive power of investor sentiment for bitcoin returns: Evidence from COVID-19 pandemic. *Technological Forecasting and Social Change, 184*, Article 121999.
Breiman, L. (1996). Bagging predictors. *Machine Learning, 24*(2), 123–140.
Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). Association for Computing Machinery.
Cohen, B. (2017). The rise of alternative currencies in post-capitalism. *Journal of Management Studies, 54*(5), 739–746.
Copestake, A., Furceri, D., & Gonzalez-Dominguez, P. (2023). Crypto market responses to digital asset policies. *Economics Letters, 222*, Article 110949.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273–297.

Dabla-Norris, E., Ji, Y., Townsend, R. M., & Unsal, D. F. (2021). Distinguishing constraints on financial inclusion and their impact on GDP, TFP, and the distribution of income. *Journal of Monetary Economics, 117*, 1–18.

Das, M., & Mohapatra, S. (2003). Income inequality: The aftermath of stock market liberalization in emerging markets. *Journal of Empirical Finance, 10*(1–2), 217–248.

Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. *Finance Research Letters, 26*, 145–149.

Demirgüc-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank.

El-Morshidy, A. M., Moghrabi, I. A., & Mostafa, M. M. (2024). An empirical investigation of the determinants influencing cryptocurrency adoption in Kuwait. *International Journal of Business Information Systems, 46*(2), 179–202.

Foley, S., Frijns, B., Garel, A., & Roh, T. Y. (2022). Who buys bitcoin? The cultural determinants of bitcoin activity. *International Review of Financial Analysis, 84*, Article 102385.

Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies, 32*(5), 1798–1853.

Galanti, S., & Özsoy, Ç. Y. (2023). Can Blockchain help improve financial inclusion? A comparative study. *Journal of Economic Issues, 57*(2), 438–449.

Gemayel, R., & Preda, A. (2024). Herding in the cryptocurrency market: A transaction-level analysis. *Journal of International Financial Markets Institutions and Money, 91*, 101907.

Griffin, J. M., & Shams, A. (2020). Is bitcoin really untethered? *The Journal of Finance, 75*(4), 1913–1964.

Gurley, J. G., & Shaw, E. S. (1955). Financial aspects of economic development. *The American Economic Review, 45*(4), 515–538.

Hayes, A. (2017). Cryptocurrency value formation: An empirical analysis leading to a cost of production model for valuing bitcoin. *Telematics and Informatics, 34*(7), 1308–1321.

Henry, C. S., Huynh, K. P., & Nicholls, G. (2018). Bitcoin awareness and usage in Canada. *Journal of Digital Banking, 2*(4), 311–337.

Horky, F., Dubbick, L., Rhein, F., & Fidrmuc, J. (2023). Don't miss out on NFTs?! A sentiment-based analysis of the early NFT market. *International Review of Economics and Finance, 88*, 799–814.

Horky, F., Mutascu, M., & Fidrmuc, J. (2021). Pandemic versus financial shocks: Comparison of two episodes on the bitcoin market. *Applied Economics Quarterly, 67*(2), 113–141.

Huber, P. J. (1981). *Robust statistics*. John Wiley & Sons.

Kara, A., Zhou, H., & Zhou, Y. (2021). Achieving the United Nations' sustainable development goals through financial inclusion: A systematic literature review of access to finance across the globe. *International Review of Financial Analysis, 77*, Article 101833.

Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2022). Measuring digital financial inclusion in emerging market and developing economies: A new index. *Asian Economic Policy Review, 17*(2), 213–230.

Kibriya, A. M., Frank, E., Pfahringer, B., & Holmes, G. (2004). Multinomial Naive Bayes for text categorization revisited. In G. I. Webb, & X. Yu (Eds.), *AI 2004: Advances in artificial intelligence* (pp. 488–499). Springer.

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives, 15*(4), 143–156.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association, 94*(448), 1296–1310.

Kukacka, J., & Kristoufek, L. (2023). Fundamental and speculative components of the cryptocurrency pricing dynamics. *Financial Innovation, 9*(61).

Le Roux, N., Schmidt, M., & Bach, F. (2013). *A stochastic gradient method with an exponential convergence rate for finite training sets*. arXiv preprint arXiv:1202:6258.

Lenka, S. K., & Barik, R. (2018). Has expansion of mobile phone and internet use spurred financial inclusion in the SAARC countries? *Financial Innovation, 4*(5), 1–19.

Lu, W., Niu, G., & Zhou, Y. (2021). Individualism and financial inclusion. *Journal of Economic Behavior & Organization, 183*, 268–288.

McCallum, A., & Nigam, K. (1998). A comparison of event models for Naive Bayes text classification. In *Proceedings of the AAAI-98 workshop on learning for text categorization* (pp. 41–48). Association for the Advancement of Artificial Intelligence. AAAI Technical Report WS-98-05.

Nguyen, L. T. M., & Nguyen, P. T. (2024). Determinants of cryptocurrency and decentralized finance adoption-a configurational exploration. *Technological Forecasting and Social Change, 201*, Article 123244.

Ogunode, O. A., Iwala, A. T., Awoniyi, O. A., Amusa, B. O., Omosebi, T. R., Kassim, S. K., & Akintoye, R. I. (2022). Cryptocurrency and global practices: Lessons for Nigeria. *South Asian Journal of Social Studies and Economics, 15*(1), 7–28.

Patel, R., Migliavacca, M., & Oriani, M. E. (2022). Blockchain in banking and finance: A bibliometric review. *Research in International Business and Finance, 62*, Article 101718.

Rella, L. (2019). Blockchain technologies and remittances: From financial inclusion to correspondent banking. *Frontiers in Blockchain, 2*(14).

Rennie, J. D. M., Shih, L., Teevan, J., & Karger, D. R. (2003). Tackling the poor assumptions of Naive Bayes text classifiers. In *Proceedings of the Twentieth International Conference on Machine Learning (ICML-2003). Washington, DC*.

Riedmiller, M. (1994). Advanced supervised learning in multi-layer perceptrons — From backpropagation to adaptive learning algorithms. *Computer Standards & Interfaces, 16*(5), 265–278.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In *Proceedings of the IEEE international conference on neural networks* (pp. 586–591). IEEE.

Rish, I. (2001). An empirical study of the Naive Bayes classifier. In *Proceedings of the IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence* (pp. 41–46). Seattle, WA.

Saiedi, E., Broström, A., & Ruiz, F. (2021). Global drivers of cryptocurrency infrastructure adoption. *Small Business Economics, 57*, 353–406.

Sapkota, N. (2022). News-based sentiment and bitcoin volatility. *International Review of Financial Analysis, 82*, Article 102183.

Sarma, M., & Pais, J. (2011). Financial inclusion and development. *Journal of International Development, 23*(5), 613–628.

Scholkopf, B., Smola, A. J., Williamson, R. C., & Bartlett, P. L. (2000). New support vector algorithms. *Neural Computation, 12*(5), 1207–1245.

Sockin, M., & Xiong, W. (2023). Decentralization through tokenization. *The Journal of Finance, 78*(1), 247–299.

Su, C. W., Yang, S., Qin, M., & Lobonţ, O. R. (2023). Gold vs bitcoin: Who can resist panic in the US? *Resources Policy, 85*, Article 103880.

Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development (IMF Working Paper No. 2016/005)*. International Monetary Fund.

Valickova, P., Havranek, T., & Horvath, R. (2015). Financial development and economic growth: A meta-analysis. *Journal of Economic Surveys, 29*(3), 506–526.

Vidal-Tomás, D. (2021). Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis. *Finance Research Letters, 43*, Article 101981.

Vincent, O., & Evans, O. (2019). Can cryptocurrency, mobile phones, and internet herald sustainable financial sector development in emerging markets? *Journal of Transnational Management, 24*(3), 259–279.

Wahyuni, M. T., Ridwan, E., & Salim, D. F. (2024). US Macroeconomic Determinants of Bitcoin. *Innovations, 21*(2), 240–252.

Wang, J. N., Vigne, S. A., Liu, H. C., & Hsu, Y. T. (2024). Hacks and the price synchronicity of bitcoin and ether. *The Quarterly Review of Economics and Finance, 95*, 294–299.

Wong, L. W., Tan, G. W. H., Lee, V. H., Ooi, K. B., & Sohal, A. (2020). Unearthing the determinants of Blockchain adoption in supply chain management. *International Journal of Production Research, 58*(7), 2100–2123.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Yang, J., Wu, Y., & Huang, B. (2023). Digital finance and financial literacy: Evidence from Chinese households. *Journal of Banking & Finance, 156*, Article 107005.

Yermack, D. (2018). *FinTech in sub-saharan Africa: What has worked well, and what hasn't* (p. w25007). National Bureau of Economic Research.

Yue, P., Korkmaz, A. G., Yin, Z., & Zhou, H. (2022). The rise of digital finance: Financial inclusion or debt trap? *Finance Research Letters, 47*, Article 102604.