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The Impact of Financial Access on the Cryptocurrency Adoption Rate

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Abstract. With a growing interest in cryptocurrencies, investigating the driving factors behind the adoption decision becomes more central. Our paper explores the potential importance of financial access by implementing an IV approach on a cross-country dataset, using smartphone penetration as an instrument. We find that financial access has a significant negative impact on the adoption rate of cryptocurrencies. However, when focusing solely on bitcoin, the relationship remains significant but turns out positive. Our findings suggest that specific cryptocurrencies are used for different purposes. While some may be essential in completing cross-border transactions, others may be more useful as investment vehicles. In addition, different ways of measuring the dependent variable are explored. By examining the existing methods of computing the adoption rate, we find similarities only for countries with low levels of cryptocurrency adoption. We believe that country-specific events and characteristics, combined with underlying methodological differences, explain the discrepancies found.

Keywords: Financial Access, Cryptocurrency, Bitcoin, Money.

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1. Introduction

Over the last decade, cryptocurrencies have become a central topic, and the adoption rate is taking off around the world. Focusing on the development over the past few years, Goschenko (2021) states that the number of global cryptocurrency users has increased dramatically and reached 221 million¹ in the first half of 2021. As the growth has been accelerating, it is interesting to study what forces drive the adoption decision of cryptocurrencies. By doing so, we attempt to uncover insights crucial for understanding the use of cryptocurrencies and whether their importance differs between the West and the rest. How does financial access affect the cryptocurrency adoption rate among individuals? Our paper aims to explore the answer to this question by empirically determining its effect.

In our study, the main variable of interest is financial access. We define it as the ability to use financial services (e.g. saving, borrowing, and completing transactions). We propose two ways of capturing the entirety of the concept in a single metric. Either by the share of adults who have completed a transaction digitally, or by the share of adults holding an account at a financial institution or mobile-money-service provider. For the remainder of this paper, we refer to financial access when considering the concept, whereas account ownership and digital transactions refer to specific metrics. When inspecting descriptive statistics on financial access, there seem to exist differences across countries. Therefore, it is interesting to investigate what effect increasing financial access has on the cryptocurrency adoption rate. In the theoretical framework, we propose that the relationship is negative since increasing the level of traditional financial access in a country should reduce its citizens' demand for alternative solutions.

To examine the nature of the relationship, we implement an instrumental variables approach with account ownership as the endogenous variable and the cryptocurrency adoption rate (CAR) as the dependent variable. The dependent variable is retrieved from Statista (2020b) and measures the adoption rate using a sample survey method and a sample size of 55 countries. However, to obtain causal estimates of the effect of financial access on the adoption rate, a source of exogenous variation is needed to instrument for the endogenous variable. Such an instrument should affect the adoption rate only through the channel of financial access to be valid. It should also yield a significant first-stage regression estimate to be relevant.

¹As can be noted, the reported figures differ depending on the data source and method used to estimate the number of cryptocurrency users. The main reason for the discrepancies in estimates is the fact that one person, in theory, can generate an infinite number of exchange and wallet accounts to hold cryptocurrencies. Because of the decentralised nature and the anonymity connected to the accounts, it is practically impossible to associate a single person to a particular account unless the owner publicly states to own a wallet address or complete any action disclosing that the person is the owner.

As an instrument for financial access, smartphone penetration is proposed.

In order to strengthen our results based on the relatively small sample on CAR, we also use a cryptocurrency adoption index (CAI) provided by Chainalysis (2020) as the dependent variable in our paper. The CAI is created using on-chain² data on trading, deposits and transaction volume. To explore similarities and differences between the two datasets, we run the same regressions for CAI as CAR, constraining the dataset to the same countries³. Descriptive statistics, correlations, and scatter plots to further examine the connection between the datasets is also provided. Our findings will indicate whether the two ways of measuring the dependent variables yields similar results or not. If they do, it may offer an option to choose one data collection method over the other or provide researchers with the prospect of deciding on a dataset depending on the aim of a specific study. Also, it should strengthen our results on the relatively small sample we are using if they yield similar results.

Bitcoin trading volume per capita (BTV) is also used as the dependent variable to investigate if it yields similar results. Any deviation in outcomes would indicate that individuals use bitcoin and altcoins⁴ for different purposes depending on the degree of financial access in their country or that trading volume per capita is not a good proxy for the adoption rate. In the theoretical framework, we propose that the relationship between financial access and BAR should turn out positive. One explanation for this difference would be the functioning of bitcoin as mere financial speculation, as proposed by Glaser et al. (2014), Baur et al. (2017) and Cheah & Fry (2015). By increasing financial access, traders and investors seeking exposure to the asset gain increased opportunities to reach it.

The first contribution of our paper is that our findings will provide insights into why individuals own cryptocurrencies by exploring the impact of financial access. Are cryptocurrencies to the benefit of unbanked citizens in countries with low financial access? Perhaps it offers individuals the possibility to start saving or make it cheaper and easier to transact. Or are cryptocurrencies to the benefit of the banked population in countries with already developed financial opportunities? It may be an asset class only providing improved possibilities for speculative investments. The cross-country focus is interesting because Al-amri et al. (2019) concluded in their paper that a limitation of previous literature is the lack of geographical regions included in the datasets used in empirical analyses.

Our second contribution is to shed light on the similarities and differences of the only two competing metrics of cryptocurrency adoption. It is of great importance since measuring the adoption of cryptocurrencies first began in 2020, and the methods used by the two metrics are different. Whereas CAR is estimated using a survey based on a random sample covering 55 countries, CAI is measured using quantitative data related to cryptocurrency wallet activity covering 139 countries. Thus, discovering similarities or differences may be of interest for future research when deciding on which metric for cryptocurrency adoption to use in specific settings.

To our knowledge, our paper is first to explore the effect of financial access on the adoption of cryptocurrencies using an instrumental variables approach. As Al-amri et al. (2019) conclude that there is a need for more quantitative research to determine the driving factors behind CAR, our paper will have a quantitative rather than

²On-chain refers to actions taking place on a blockchain.

³Due to the missing observation of Taiwan, CAI will run on 54 observations.

⁴Cryptocurrencies other than bitcoin.

a qualitative approach. The reason behind the lack of empirical papers is partly because the cryptocurrency concept is a relatively new idea with a history commencing in 2008 when Nakamoto (2008) submitted his whitepaper on Bitcoin. Another contributing factor is that the data collection on the adoption of cryptocurrencies on a global scale began in 2020. Our paper is also first to compare competing ways of measuring the adoption rate and discuss the implications of any differences. Hence, it allows us to discover whether entirely different ways of measuring the dependent variable give rise to the same results.

In contrast to previous literature focusing on specific countries or sub-groups, we use cross-sectional data and explore what effect financial access has on the adoption rate of cryptocurrencies globally. Thereby, we can observe whether the finding from previous studies, indicating that financial access is a crucial factor, is valid on a global scale or whether its importance differs from one country to another. Inspecting the direction of the effect of financial access on CAR allows us to distinguish if it is more attractive for citizens in countries with low levels of financial access to adopt cryptocurrencies, as proposed by Pandya et al. (2019), Nadeem et al. (2021) and Campbell-Verduyn (2018).

Another aim is to explore and discuss different ways of measuring financial access, updated to a digitalised post-mobile-money-revolution world. We investigate whether our results differ when using a digital transaction-related variable to measure the degree of financial access, compared to using data on account ownership at a financial institution or mobile-money-service provider. By doing so, we provide a better understanding of the importance of transactions compared to saving, borrowing, and other branches of financial access.

Due to the emerging nature of our field of study, there are some concerns with our empirical analysis we would like to highlight. Since there is a limited number of studies relevant to our research question, we have in many instances had to make novelty decisions on how to tackle practical and theoretical issues related to our empirical approach. One apparent obstruction is the availability and quality of the data for our dependent variable. Not only has it just begun to be measured and therefore offers little to no time variation, but the methods of computing the adoption rate are also still being developed and may improve over time. At least, this is the case when considering estimations made from quantitative inputs (e.g. CAI and BTV). There are also inherent problems specific to the two ways of measuring the dependent variable. For CAR, we are confident that the survey method offers a procedure that estimates the share of the population adopting cryptocurrencies, but with potential for false reporting and requiring time and effort that may be a paramount factor in CAR being a relatively small sample. When considering CAI, there are issues connected to their quantitative approach. It is difficult to estimate the adoption rate, and their metric relies on data that may be difficult to access. Besides, CAI may not capture the adoption rate, but something strongly correlated to it. Even though there are apparent issues with the dependent variables, we decide to explore the existing options in our theoretical framework and conduct a comparative analysis of the two competing methods.

Another potential issue is the choice of instrument. As we are first to explore any cross-country differences in an instrumental variables approach, there is no prior research we can look towards to find appropriate instruments. Instead, we had to find an instrument showcasing a strong first-stage relationship and think

thoroughly about how the exclusion restriction may be violated. Smartphone penetration is found to be a relevant instrument for financial access. The F-statistic of the first-stage is 41.399, and the correlation is 0.827, indicating a strong first-stage relationship. We also believe that smartphone penetration should have a negative effect on the adoption rate only through developing the financial access of a country's population and that the IV approach improves upon the OLS. Nevertheless, it is essential to consider potential issues with the validity, as this assumption cannot be formally tested. We are aware that some may be concerned that certain unobservable factors are correlated with the dependent, endogenous and instrumental variables (e.g. income per capita) or that there are other channels through which the instrument influences the dependent variable. Being first means that there is always a risk of encountering such quandaries, and had there existed data for more periods, we would have preferred to use panel data methods. Instead, we attempt to address potential issues and refute some preconceived notions.

Our results show that financial access has a significant and negative effect on an individual's choice to adopt cryptocurrencies, using CAR and CAI as dependent variables. Another finding is that financial access has a significant but positive effect when using bitcoin trading volume per capita as the dependent variable. The findings are in line with discoveries in previous research. Bitcoin functions as a speculative asset, but adopting cryptocurrencies is more attractive for individuals with lower financial access. This result holds for both account ownership and digital transaction.

Concerning the different methods of measuring the dependent variable, our results indicate that CAR and CAI are somewhat similar, considering countries with a lower adoption level of cryptocurrencies. The correlation is positive but weak (0.3) when including observations with high CAI scores. However, when excluding the countries with the highest CAI scores, the correlation increases dramatically to 0.63. A potential reason for this result is the inherent differences in the methods of computing the two metrics. Whereas CAR is an absolute measure of the adoption rate, with a baseline starting from 0 (indicating no adoption), CAI is a relative measure with a baseline of 1 (designated to the country with the highest adoption) and issuing scores between 0 and 1 for the other nations in respect to the highest-scoring country. Country-specific factors may partially explain why particular observations experience divergent placements in CAR and CAI.

We have organised the remainder of the paper in the following way: Section 2 gives a brief historical perspective on money and the evolution of cryptocurrencies. It further describes some basic concepts of a cryptocurrency. Section 3 provides a literature review of existing studies within the field. In this part, we also present two hypotheses. Section 4 outlines the methodology and presents the data that we use. Section 5 presents the main results. Section 6 analyses the results, comments on the differences and similarities concerning previous findings, limitations, and suggests future research within the area. Finally, section 7 concludes by presenting our main takeaways.

2. Background

2.1 The Introduction of Money

In an economy, money generally acts as a medium of exchange and is often referred to as currency. According to Chen (2021), the most common type of money today is fiat currency. It is a type of currency issued by a government. However, it does not have any intrinsic value, in sharp contrast to a commodity made from valuable material such as silver or gold. Instead, the value relies more on a government's creditworthiness and other central authorities, as stated by the Corporate Finance Institute (2021). Over the history of money, there has been a continuous battle between advocates of commodities and fiat currencies. After the Bretton Woods system concluded, fiat currency has ruled sovereign for almost half a century. Whether it will continue to be that way remains a question.

Chown (1994) and Davies (2005) present an extensive history of the evolution of money. In detail, they explain the drawbacks of barter in commodities and how the introduction of fiat currencies helped solve some issues, e.g. agreeing on exchange rates for products. Even though this may not be a central issue for smaller economies with few goods, deciding on exchange rates for specific trades becomes increasingly tricky as more goods are introduced on the market. One could argue that this remains a problem in the current monetary system with the many existing local currencies, although some currencies are more critical than others. Similarly, it could be argued that the introduction of thousands of cryptocurrencies has only added to the problem. However, remember that it is an infant industry, with coins and tokens having different use cases. Bitcoin is the most used cryptocurrency and could be compared to the importance of the U.S. dollar when considering fiat currencies.

Davies (2005) argues that storing value is another disadvantage of barter in commodities because it is more costly than fiat currencies. Although this is true, he refers to the accounting cost, not considering the potential cost of inflation when it comes to fiat currencies. His argument favouring fiat currencies of bank deposits earning returns is not valid nowadays since the inflation rate exceeds the deposit rate offered by banks in many developed countries. One explanation for this could be that a lot has happened since he published the book in 2005. Nonetheless, even if he disregarded that fact, he forgot to consider the differences in financial access for people living in different parts of the world. People holding fiat currency do not all have the same possibilities to store it by saving at a financial institution, and the cost differs as well, which is clear from the book by Campbell-Verduyn (2018).

Similarly, Davies (2005) shed light on some drawbacks of using fiat currencies instead of commodities. One example is that they do not have any intrinsic value, in

stark contrast to commodities. There is also a higher risk of eroding the value over time due to inflation or hyperinflation in severe cases. Over the past century, multiple events of unstoppable inflationary spirals have occurred. He argues that the risk of hyperinflation today is more pronounced in developing countries. Chown (1994) cover some examples in his book, including the most known story of Germany in the 1920s. He also adds to the nuanced discussion regarding the issues of debasement considering commodities, focusing on the use of precious metals in coins. In contrast to what some may think, debasement is historically not a concept exclusive to fiat currencies. The difference is how the debasement is occurring. For a fiat currency, the diminishing value of a specific paper note stems from printing more paper notes. Although mining a specific precious metal has a slightly negative effect on the value of precious metal-based coins, a more potent effect relates to lowering the amounts of precious metal contents.

Deflationary cryptocurrencies⁵ may, at least theoretically, have the potential to solve some of the issues outlined above. They have the desired property of a capped inflation rate and a maximum supply, an upgrade compared to fiat currencies. Suppose such cryptocurrencies were to replace local fiat currencies. In that case, this feature could stop governments and central banks from encountering hyperinflation, and it would also ensure that they reach any inflation or deflation target. Pandya et al. (2019) underline that it is also easier and cheaper to store value and complete transactions using cryptocurrencies compared to commodities. Furthermore, as noted by Abramova & Böhme (2016), bitcoin (and cryptocurrencies in general) can be used to complete transactions at any time of the day, any day of the year. These properties offer significant improvements from commodities and fiat currencies that lack this feature⁶.

So, does cryptocurrencies offer an improvement over commodities and fiat currencies in functioning as money? On the one hand, Pandya et al. (2019) suggest that the lack of a central bank may result in volatile prices for cryptocurrencies. In turn, they may be challenging to use as means of transaction because the value per unit of a specific cryptocurrency can change dramatically over a short period. On the other hand, they highlight the ease of theft as being a disadvantage of fiat currencies and commodities compared to cryptocurrencies. Stealing cryptocurrencies from a wallet protected by unique keys⁷ and two-factor-authorisation⁸ is, in general, more

⁵Cryptocurrencies where a fundamental property of their code caps the total supply at a number and potentially burns some of the tokens or coins when used. In particular cases, even cryptocurrencies with inflation are included in this basket if there is a cap on the inflation rate, which converges to a capped total supply. Bitcoin is one example of the latter, where there is (potentially) inflation as of today but will converge to its capped supply of 21 million bitcoins in the future. It is uncertain if there is inflation because the rate at which bitcoins are lost (e.g. due to owners forgetting their passwords) is uncertain. Hence, it is difficult to evaluate if the coded inflation rate, increasing the total supply, is larger than the rate at which bitcoins are lost.

⁶For example, in some cases, transactions can only be made during certain times of the day and not on weekends.

⁷The owner can access a wallet using a set of keys that allow sending, receiving and depositing cryptocurrencies. A set of private keys enable the owner to send transactions using cryptocurrencies in their wallet. In contrast, public keys are used to receive transactions in cryptocurrencies to their wallet address. Usually, these keys are made up of a long string of letters and numbers, unique for every created wallet address.

⁸In order to access a cryptocurrency wallet, most wallet providers offer owners the option to require a second step of authentication, in addition to a unique seed phrase (which is a simpler version of a private key). An owner can receive greater security by connecting a phone number to

complicated than stealing cash. Furthermore, Pandya et al. (2019) and Abramova & Böhme (2016) highlight that cryptocurrencies allow for faster transactions at a lower cost than fiat currencies or commodities. Hence, cryptocurrencies offer enhancements over commodities and fiat currencies as they reduce the cost of storing value, reduce the risk of hyperinflation eroding the value and allow for completing transactions at a lower cost. However, the volatile prices may be deterring individuals from using cryptocurrencies over fiat currencies or commodities. Also, because of the large number of existing cryptocurrencies, some may be more appropriate in serving as money than others.

Due to a great deal of heterogeneity amongst cryptocurrencies, certain features are making them distinguishable. One of the many is the total supply. While some cryptocurrencies are deflationary, others are inflationary⁹. The characteristics of distinct cryptocurrencies mainly depend on their purpose, and differentiation can arise due to the blockchain trilemma¹⁰.

Note that certain features of cryptocurrencies are similar to those of commodities. Due to the vast heterogeneity in cryptocurrencies, it is challenging to present characteristics that hold for every existing coin. Focusing on particular cryptocurrencies makes it easier to find features resembling those of commodities. For instance, mining bitcoin is similar to mining gold in terms of cost, risk, energy and difficulty in finding the underlying asset, according to Wolfgang et al. (2019). Furthermore, bitcoin has a capped total supply, just like gold.

2.2 The Rise of Cryptocurrencies

In 2007-2008 the financial crises resulted in a prolonged period of economic turmoil and a great recession worldwide. Before the financial crisis, people had their trust in banks. As a result of the crisis, financial markets failed, unemployment rates rose dramatically, banks collapsed, and millions of people lost their savings. Consequently, the confidence in financial institutions was hurt. With a growing interest in finding an alternative to fiat currencies that was not influenced by central authorities, cryptocurrencies emerged, according to Reiff (2021).

The first concept of a cryptocurrency was introduced in late 2008 by Nakamoto (2008) when he published his white paper on Bitcoin. Today, it remains the largest (by market capitalisation) and most well-known cryptocurrency. Following the inception of Bitcoin, a large bulk of cryptocurrencies were created. Blockspot (2021) estimate that there exist more than ten thousand cryptocurrencies and over 75 mil-

the account or using a third party authentication service.

⁹These include cryptocurrencies without the properties of deflationary cryptocurrencies. Instead, they add new coins to their system over time and, therefore, has the potential of providing infinite supply, according to The-blockchain.com (2021).

¹⁰The idea is that a single cryptocurrency cannot provide all of the three desired properties of a cryptocurrency. These include decentralisation, security, and scalability. Instead, it can only provide two of the three properties. For instance, some cryptocurrencies have been created to improve the scalability property, which is lacking in the case of bitcoin (focusing on security and decentralisation). Many projects and individuals are currently working hard to solve this problem, and one of many existing potential solutions was proposed by Li et al. (2020), focusing on ensuring security to sharding (a scalable database partitioning technique used in some cryptocurrencies) schemes.

lion cryptocurrency wallets¹¹ users.

The cryptocurrency revolution in developing countries can be viewed as a continuation of the mobile money revolution in East Africa that Campbell-Verduyn (2018) covers extensively. In Kenya, the ability to complete transactions and access credit using a simple text messaging system¹² offered many unbanked citizens an alternative to traditional financial institutions or the informal sector. Today, mobile-money-service providers remain popular in large parts of Africa and grow steadily across the continent. We would argue that cryptocurrencies accelerate the mobile money revolution, as it provides a faster and cheaper mechanism to send transactions than using text messaging systems.

Cryptocurrencies can be considered digital currencies that are encrypted and often decentralised. According to Pandya et al. (2019), cryptocurrencies are an alternative to commodities and fiat currencies issued by the government. However, Glaser et al. (2014), Baur et al. (2017) and Cheah & Fry (2015) would argue that certain cryptocurrencies are only speculative assets. The main difference between fiat currencies and cryptocurrencies is their inherent value. As mentioned before, the government supports fiat currency, and the trust in central authorities are essential for its value. Cryptocurrencies, however, derive their value from their main feature known as blockchain technology, according to Wolfgang et al. (2019). Blockchain technology generally allows for online payments between two parties without a bank, or other financial institutions, to confirm the transactions. Its value is determined by the supply and demand in the market, as stated by Baghla (2017) and Glaser et al. (2014). The blockchain can act as a database where information is collected, mainly recording ledger payments. Wolfgang et al. (2019) argue that it is more efficient than the traditional type of centrally managed ledgers. The blockchain structure is often known as distributed ledger technology and provides more security because it is more shared and distributed rather than centralised.

3. Theoretical Framework

3.1 Previous Literature

As bitcoin remains the largest cryptocurrency by market capitalisation, holding a share of 41.4% of the entire cryptocurrency market¹³, most of the current literature focuses on the adoption of bitcoin specifically. Meanwhile, few research papers target the adoption of cryptocurrencies in general. Therefore, we highlight the key

¹¹It is a place where an individual can store cryptocurrencies, trade, and complete transactions. There exist both software and hardware versions, known as hot or cold wallets, respectively. Software wallets are less secure but allow for faster transactions than hardware wallets because they are connected to the internet.

¹²The text messaging system allows users to transfer phone credits to other users and works as a cash alternative, allowing people without access to bank accounts to transfer funds digitally.

¹³The number was retrieved from CoinMarketCap (2021) on the 14th of September 2021.

findings from past studies, focusing on either bitcoin or cryptocurrencies, relevant to our research question.

Certain essential features of some cryptocurrencies, making them an alternative to fiat currencies for individuals, are highlighted in a paper by Pandya et al. (2019). These include the absence of inflation because of total supply caps and the difficulty in stealing accumulated digital wealth from a cryptocurrency wallet because of the strong security offered by unique keys and two-factor-authorisation. Another essential feature for individuals adopting cryptocurrencies is the ability to make cross-border transactions at a faster speed and at a lower cost than fiat transfers using financial institutions. In contrast to traditional bank transfers in fiat currencies that can take up to several days, Pandya et al. (2019) state that a transaction in bitcoin only takes 10 to 30 minutes¹⁴. According to Abramova & Böhme (2016), it is the fact that the transactions take place online directly between two parties that make it operate at a faster speed, and thanks to bitcoin's consensus mechanism (a method used by a cryptocurrency to provide security and verification of transactions on its blockchain), there is no need for any financial institution or other intermediaries to execute the transaction. Similar to mobile-money-services, Pandya et al. (2019) argue that these improvements are more substantial in developing countries, where it is less common to have access to traditional banking services and where people often work far away from their families.

Based on a study in China¹⁵ by Nadeem et al. (2021), the critical feature of cryptocurrencies in offering instant transactions at low fees also holds for the bitcoin adoption rate (BAR). Using survey data¹⁶ and the technology acceptance model¹⁷, they find that transaction processing significantly affects the adoption of bitcoin. Abramova & Böhme (2016) also studies potential factors impacting the BAR based on the technology acceptance model. In line with the findings of Nadeem et al. (2021), the feature of working as a means of transaction¹⁸ is a significant factor in

¹⁴Some cryptocurrencies offer instant transactions, which means that a transaction is instantly settled within minutes, and in other cases, even seconds.

¹⁵The focus on China regarding bitcoin is interesting, as it has been targeted by the Chinese government on several occasions over the past years in more or less successful attempts to decrease the usage of bitcoin. For instance, Pandya et al. (2019) write that banks were not allowed to handle transactions in bitcoin starting from late-2013 due to its decentralised nature. Exchanges were not allowed to offer trading in bitcoin in late-2017 due to its anonymity feature, which could be used for criminal purposes. In mid-2021, the Chinese government announced a ban on bitcoin mining because of its high emissions. Lastly, they announced a ban on all transactions using cryptocurrencies in late-2021 due to its speculative nature. Interestingly, individuals seeking exposure to cryptocurrencies within China's borders always find a way to access cryptocurrencies, despite any ban. Nadeem et al. (2021) identify the use of virtual private networks as one example. A limitation of the paper is the survey data used in their empirical part, which is based on the residents living in the city. That could cause a possibility that the results would have been different if they had included residents in rural areas. The targeted city was Hefei in Anhui.

¹⁶The study focuses on individuals with an understanding of Bitcoin. The final sample that they used consisted of 385 responses out of 450.

¹⁷It is a model used to determine how users adapt to new technology, primarily focusing on perceived usefulness and perceived ease of use.

¹⁸Approximately 67.4% of the 86 respondents surveyed stated that they used bitcoin to transact. They compared the answers to another study with 6395 respondents to check whether they had captured a somewhat representative sample. They found that women were underrepresented in their sample, as only 2.3% of their respondents were female. In contrast, the other study suggested that this number should be closer to 33.3% when considering people hearing about, understanding, or owning bitcoin. That is important to keep in mind, as their results may have been impacted by

explaining the BAR in Europe. In addition, Khairuddin et al. (2016) acknowledge monetary revolution, perception of bitcoin's actual value and user empowerment being three factors that seem to explain why people own bitcoin¹⁹.

Nadeem et al. (2021) also highlights, similar to Pandya et al. (2019), the importance of making cross-border transactions, which is far beyond what traditional banks can offer in terms of fiat currencies features, primarily for unbanked inhabitants of developing countries. Abbasi et al. (2021) found in their paper that performance expectancy and price value are some of the factors that affect the adoption of cryptocurrencies in Malaysia²⁰. As cryptocurrencies allow for faster cross-border transactions at a lower cost compared to traditional banks and fiat currencies, these requirements should already be considered fulfilled. Hence, it implies that users adopt cryptocurrencies if they find a relevant use case, solve an everyday problem, or save money. Consequently, these findings strengthen our use of financial access as a potential element affecting the cryptocurrency adoption rate. This argument is also further supported by Alzahrani & Daim (2019), where existing literature on the adoption rate of cryptocurrencies is explored. They conclude that transaction-related features, such as low fees and instant transactions, and state illegitimacy related components, such as privacy, security, and anonymity, are essential features explaining the adoption of cryptocurrencies. According to Al-amri et al. (2019), security and awareness variables, as well as monetary and government stability, are some potential drivers that can be explored further²¹. In contrast, Luther (2016) argues that cryptocurrencies will not be able to reach widespread adoption without either monetary instability or government support. An example of such government support to promote the adoption of cryptocurrencies is the recent acceptance of bitcoin as legal tender in El Salvador. Some additional factors that seem to be influential are working as an alternative to the existing banking system or as a store of value, according to Alzahrani & Daim (2019). Again, the feature of a limited total supply that puts a cap on the inflation for assets with this feature could be related to this.

However, it should be noted that a lot of the existing literature base their results on small samples and often have a qualitative focus, rather than empirical, due to the lack of existing data on the adoption rate. Hence, Al-amri et al. (2019) request more empirical focused research to explore the driving factors behind the adoption of cryptocurrencies as this vital issue makes it difficult to generalise the findings from such studies. Nonetheless, we understand that lacking continuous data gathering of cryptocurrency adoption at every level in society is one explanation for why few empirical studies have been performed on this topic.

Even though there is a lack of studies on the adoption of bitcoin, more studies including more women in their sample.

¹⁹They use a qualitative approach interviewing bitcoin users.

²⁰The study is based on a survey sample of 314 observations. Machine learning techniques and a two-stage partial least squares structural equation model are combined and compared to more common and simple logistic regression models. According to the authors, this model works better on samples that do not fulfil the conditions for other regression frameworks (e.g. normality). The study is built upon the technology acceptance model, similar to the studies by Abramova & Böhme (2016) and Nadeem et al. (2021). However, Abbasi et al. (2021) allow for more complex factors and relationships in their model.

²¹Based on a literature review on 25 research papers of CAR related studies. The paper also highlights the importance of social norms, as they are concerned that it could affect the results in many of the reviewed papers.

have mainly focused on its price performance and found that bitcoin is only a speculative asset without any fundamental value. Glaser et al. (2014) acknowledge the fact that it is challenging to value bitcoin using traditional valuation methods for fiat currencies since it lacks an interest rate set by a central bank. Instead, because of its deflationary structure with a total supply cap, the sellers and buyers only determine bitcoin's value, and the price of bitcoin can only move if there is a change in the number of sellers and buyers²². In contrast to Glaser et al. (2014), the paper by Baur et al. (2017) focus on bitcoin relative to other asset classes²³ and finds that bitcoin is uncorrelated with them all²⁴. In an attempt to explain how users interact with bitcoin, they identify six user types and provide statistics for the evolution of their ownership of bitcoin over the years that they cover. Since the groups using it as an investment are larger (and growing) than those using it for transactions, they conclude that bitcoin is a speculative asset. However, when examining the division of the user types, one can note that the dollar value of a transaction is essential, as is the number of transactions. We want to raise some concerns with this as they assume that bitcoin is only used to purchase low-end goods, although their cutoff value of 2000 U.S. dollars covers a large bulk of everyday transactions. Not only do they fail to correctly identify purchases of more expensive electronics or art as currency users, but they may also overestimate the number of investors. That may happen if an individual makes a significant transaction from one wallet to another. With their classification, that person would count as two investors, one being passive (receiving the transaction) and the other active (sending the transaction). Thus, it is uncertain whether or not they have correctly identified bitcoin users as specific types. Nevertheless, when studying the changes in proportions of user types as the price of bitcoin changes, they find results indicating that perhaps they have made a reasonable identification of user types. Although the paper by Baur et al. (2017) may have weaknesses, Cheah & Fry (2015) also find that bitcoin show signs of being a speculative asset when studying closing prices in the United States²⁵.

3.2 Hypotheses

Based on existing literature, three potential ways in which financial access can affect the adoption of cryptocurrencies is distinguished, and we condense these into two hypotheses.

H1: *Increased financial access has a negative impact on cryptocurrency adoption*

²²They use time-series data on bitcoin trading volume and prices from the largest exchange in the United States between the years 2011-2013 to figure out whether bitcoin is considered an asset or a currency by the individuals buying bitcoin for their first time. To measure new users on the network, they use data on page views on Bitcoin's Wikipedia page.

²³The asset classes they look at cover commodities, fiat currencies, stocks, and bonds.

²⁴The correlation ranges from -0.03 to 0.05. Furthermore, Baur et al. (2017) run regressions with the price of bitcoin as the dependent variable and find few significant relationships with other asset classes and years. However, this can happen due to chance alone. They focus on price data in the years 2010-2015. One should note that they are self-aware about using closing prices in the United States, as they indirectly introduce a regional focus in their study.

²⁵They use time-series data from mid-2010 to mid-2014. Instead of using Wikipedia page views as Baur et al. (2017), they use the number of Google searches on "Bitcoin".

First, it can be difficult for people in developing countries to access credit because of high-interest rates or a lack of assets to be used as collateral when applying for a loan. On the other hand, it can also be challenging to save money. Cryptocurrencies are then an option that can offer an easier, faster and cheaper way to access credit or function as a store of value, as proposed by Abramova & Böhme (2016). Since this is a more common issue in developing countries and not as much in developed countries, we believe that the effect of working as a substitute to traditional financial access should be more substantial in developing countries. Campbell-Verduyn (2018) expects cryptocurrencies to provide access to financial services for the unbanked²⁶ population living in societies characterised by high cash-use and informal sectors.

Second, cryptocurrency can also be used as an improved means of transaction compared to fiat currency, in accordance with Abramova & Böhme (2016). Following Campbell-Verduyn (2018), it is estimated that as many as 2 billion people around the world lack access to traditional financial services. The emergence of smartphones has resulted in an alternative for those to use digital mobile-money-service providers instead of analogue financial institutions, an argument supported by Abramova & Böhme (2016). Campbell-Verduyn (2018) states that cryptocurrencies are enhancing this trend, as they are an improved way of completing cross-border transactions. They offer a radical improvement over the high fees linked to cross-border transactions that mobile-money-service alternatives have failed to address. The special traits of cryptocurrencies allowing for faster and cheaper transactions than fiat currencies are fundamental to people in countries with low financial access, working as migrants in other countries for periods, with a need to send money back to their families. The paper by Nadeem et al. (2021) argues that this also holds for bitcoin specifically. As shown by a real-world example from Kenya in Campbell-Verduyn (2018), the fee for making a cross-country payment can be reduced to approximately 2% using a cryptocurrency such as bitcoin, compared to traditional methods with fees ranging from 5-30%. A reason for this cut in fees is argued to be the reduction in intermediaries when executing a transaction. Subsequently, we believe that this effect should be more critical in countries with lower financial access, as suggested by Nadeem et al. (2021).

H2: *Increased financial access has a positive impact on bitcoin adoption*

When considering bitcoin specifically, financial access can have a positive effect on the adoption rate. For instance, if it is only functioning as a speculative investment, as proposed by Glaser et al. (2014), Baur et al. (2017) and Cheah & Fry (2015), we expect that increasing the financial access should increase BAR because of the expanding opportunities for traders and investors to access the asset. Also, Abramova & Böhme (2016) and Alzahrani & Daim (2019) state that working as an investment is one potential use-case of bitcoin. In contrast to the other papers, they argue that it also has a potential value from working as an improved means of

²⁶Those without any prior experience of services provided by financial institutions.

transactions.

4. Method and Data

4.1 Data

Dependent Variable

We retrieved the principal measure of the cryptocurrency adoption rate (CAR) from the Global Consumer Survey from 2020, collected by Statista (2020b). Within each of the 55 countries, the number of sampled elements is between two thousand and twelve thousand. All participants were given a question regarding their use and ownership of financial products (see Appendix A.1) over the past year. The share of respondents stating that they own, or have used, any cryptocurrency is used in our paper. An overview of the underlying data and descriptive statistics are provided in Table 4.1. In column 1, the six most important variables to our study are listed. The first three variables listed are used to capture the adoption rate, followed by the two alternative measures of financial access. Smartphone penetration concludes the list. Column 2 in the table provides the mean value. Columns 3 and 4 give the lowest and highest values, respectively. Finally, column 5 provides the standard deviation. From this table, we notice that the mean cryptocurrency adoption rate is in general low (9.7%) compared to the share of the population with account ownership (77.2%) and the smartphone penetration rate (52.6%). Descriptive statistics of the control variables are provided in Table ?? in Appendix A.7.

Table 4.1: Descriptive statistics

(1) Variable	(2) No. Obs	(3) Mean	(4) Min	(5) Max	(6) Std
CAR	55	0.097	0.037	0.319	0.051
CAI	54	0.213	0.033	0.931	0.190
BTV	36	1.060	0.018	4.603	1.106
AO	55	0.772	0.213	0.999	0.232
DT	55	0.641	0.060	0.990	0.297
SP	55	0.526	0.067	0.806	0.189

The table contains descriptive statistics for variables used in our study. Provided are measures on the mean value, the lowest and highest value, and the standard deviation. CAR stands for cryptocurrency adoption rate, CAI for cryptocurrency adoption index, BTV for yearly bitcoin trading volume per capita (measured in dollars), AO for account ownership, DT for digital transactions and SP for smartphone penetration.

The countries in our dataset include both developed and developing countries from a wide range of world regions. We illustrate the adoption rate of cryptocurrencies by individual countries in Figure 4.1. There is no accessible data for grey-coloured countries, and the darker a country is coloured blue, the higher is the CAR. From Figure 4.1 and the descriptive statistic showcased in it, a few concerns need to be taken into consideration. Most importantly, some regions are more represented in our dataset than others. For instance, the data contain only five African countries, but two of these countries have the highest cryptocurrency adoption rate in our sample, Nigeria (1st place) and South Africa (4th place). A study by Hileman (2015) created an index estimating which countries have the highest potential use of Bitcoin and finds that six out of the top ten scoring countries (Nigeria included) are located in Sub-Saharan Africa. Therefore, it is no surprise that Nigeria and South Africa are scoring highly in the measure used for CAR. However, it is uncertain how the results would be affected if the dataset included more countries from Africa. Also, in Figure 4.1, note that there is no Central Asian country in our sample. If including any countries from that region, the results may be affected in any direction.

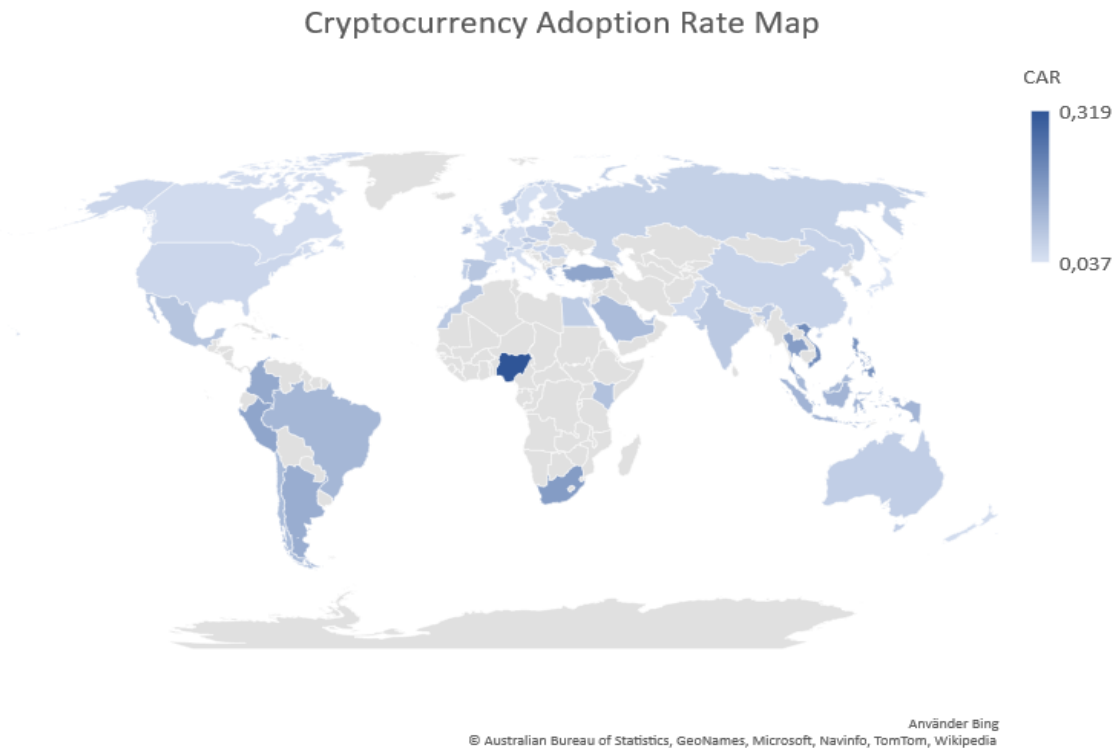


Figure 4.1: World map illustrating the cryptocurrency adoption rate using data from Statista (2020b).

In contrast to Statista (2020b) utilising a sample survey to estimate the adoption rate, Chainalysis (2020) employ a quantitative approach. By combining four metrics related to transactions and trade volume, weighted by per capita purchasing power parity, they estimate a cryptocurrency adoption index (CAI). An advantage of using their data as a dependent variable is the number of observations since they provide estimates for 139 countries, compared to Statista (2020b) where only 55 countries are covered.

The issue with CAI is that none of the metrics considers factors directly connected to the number of cryptocurrency users per country. With a focus relying heavily on transaction and trade volume, it may not capture the adoption rate, but something more or less correlated with it. An example would be the average cryptocurrency transaction value per capita. Their heavy dependence on data from independent exchanges is also problematic for future years as the number of cryptocurrency exchanges may grow with the adoption rate. If they are unsuccessful in retrieving data from a single cryptocurrency exchange in a single country, their overall estimation may be adversely affected. One might think that this is not a major problem, as every transaction should end up on the blockchain ledger. However, this reasoning is only partly true. Every transaction taking place within a centralised exchange does not count as an actual transaction and is consequently not reported on the ledger. The quantitative approach of Chainalysis (2020) would then fail to capture all transactions and underestimate the adoption rate for those countries in which they cannot access all relevant data. While working on this paper, a new batch of data for the year 2021 was released, and we provide a short comment regarding this in Appendix A.6. Most importantly, the data are not comparable because of the changes in measurements between the two years.

Another issue with CAI is the way the adoption rate is measured. As opposed to Statista (2020b), measuring CAR in terms of the proportion of the population adopting cryptocurrencies, Chainalysis (2020) gives every country a placement-based score in all categories measured (where a lower score indicates higher cryptocurrency adoption). Following this, they calculate an average. Finally, they give the overall lowest-scoring country the value one and then computes a relative index score between 0 and 1 for the other countries. The way in which this score is computed makes it strenuous to interpret any coefficient estimates from regressions economically. Expressed differently, CAR is an absolute measure of the adoption rate, whereas CAI is a relative measure and are generally more challenging to interpret.

Although there are drawbacks of CAI, we use it as a dependent variable in the regressions. The reason is that even if it may be hard to interpret the result economically, the significance and the sign of the coefficient is still of interest as it will provide insights into whether there seems to be a robust relationship between financial access and the adoption of cryptocurrencies. Furthermore, it may indicate that it is possible to collect data on CAR in different ways and reach similar outcomes. Therefore we decided to keep the observations included in the Statista (2020b) dataset ²⁷. The reason for excluding other observations is to get two comparable datasets to analyse similarities and differences.

We also run regressions using bitcoin trading volume per capita (BTV) as the dependent variable. It covers 44 countries²⁸ in 2020 by Statista (2020a) and measured in millions of U.S. dollars. We have, however, transformed this data by dividing the values by a country's population in millions to make it similar to other variables used in the regressions. Hence, the unit of measurement changes to U.S. dollars per capita. There are two differences between the CAI and BTV. First, BTV focuses solely on Bitcoin, whereas CAI focuses on all cryptocurrencies (including Bitcoin). Second, BTV only focuses on trading volume, whereas CAI includes other areas (e.g. deposit and transaction volume). Again, similar to CAI, BTV may not capture the

²⁷Since CAI have excluded Taiwan, this dataset ends up with 54 elements.

²⁸When matching this dataset to the others, we end up with 36 countries.

adoption rate, but something correlated to it. The results, using BTV as the dependent variable, will provide insights on whether there are any differences between developed and developing countries in terms of using bitcoin versus altcoins.

Independent Variables

Based on previous research, financial access seems to be important in driving cryptocurrency adoption. An issue with determining the effect is the difficulty of finding a good proxy for financial access. Traditionally, it has been measured as the possibility to use financial services, such as saving, lending, or completing transactions. Thus, it is not considering the actual use of these services, as people might have access to save or lend but may not choose to do so. The World Bank (2012) suggests that the share of the population with a bank account is a suitable measure of financial access. Arguably, a more relevant and modern measure of financial access should include access to mobile-money-services since many individuals, primarily in developing countries, lack access to financial services through a financial institution but rather have access to similar services on their mobile phones. This argument is also supported by Pandya et al. (2019) and Campbell-Verduyn (2018). While the World Bank (2012) acknowledge that considering only bank accounts may not be sufficient as a proxy variable for financial access, they also state that it may be challenging to find better alternatives due to the difficulty in collecting the data. Suggesting measurements focusing on the share of the population with bank accounts may underestimate the financial access in developing countries. A better measurement is the share of a country's inhabitants, 15 years of age or older, holding an account at a financial institution (e.g. a bank) or a mobile-money-service provider. It has been measured in a survey²⁹ by the World Bank and is included in the Global Findex Database by Demircuc-Kunt et al. (2018). This will be used as our primary variable of financial access. Including data from 159 countries in the years 2011, 2014, and 2017, it covers all of the 55 countries in the Global Consumer Survey in 2020 from Statista (2020b). The data from the Global Findex Database is constructed using random sample surveys. Again, we provide some descriptive statistics in Table 4.1.

We also suggest an alternative metric to measure financial access, which is the possibility to make transactions digitally. It has also been measured in the Global Findex Database by Demircuc-Kunt et al. (2018). The variable captures the share of a country's population, 15 years old and over, that have completed a transaction digitally within the last year. An issue is that in some cases, an individual could have access to complete a digital transaction but decide not to do so if there is a possibility to transact using cash and if this alternative is preferred. Hence, this metric could underestimate financial access, and we believe that this underestimation is more pronounced in developing countries, where digital alternatives may not be customary, and the cash-driven shadow economy is more substantial compared to developed countries. As stated by Campbell-Verduyn (2018) and Mas & Radcliffe (2010), when measuring financial access, the focus has over the past decade shifted away from access to saving and credit in favour of the possibility to make digital transactions. Consequently, it can still be interesting to explore this variable

²⁹Approximately a thousand people per country made up their sample, and the individuals were randomly selected.

as a proxy for financial access to see how this specific focus on completing digital transactions affects the result. However, one can argue that it is not capturing the entire concept of financial access. Instead, it may only recognise the access to make transactions, similar to studies by Nadeem et al. (2021) or Abramova & Böhme (2016), finding the importance of simplifying transactions in China and European countries, respectively.

Controls

A report by the World Bank (2012) states that financial access has a positive effect on economic development and income. For digital payments specifically, Morawczynski & Pickens (2009) find a positive effect on income in rural Kenya. Therefore, we should not include any variables related to economic development (e.g. GDP) as controls in our model since it would adversely affect the results working as mediators of the effect of financial access on CAR and result in biased estimates. Furthermore, none of the previous literature in our review have proposed that income should be a key driver of cryptocurrency adoption. Nevertheless, the impact of financial access on cryptocurrencies may work through the channel of income.

As argued by Bloom et al. (1998), the geography of Africa and its tropical climate is the main contributing factor for the weak economic development of Sub-Saharan African countries, compared to countries with a milder climate. They also argue that their finding holds on a global scale. Since latitude and climate zones are closely connected³⁰, an idea to indirectly include economic development is to use latitude as a control variable. However, we do not expect to capture the entire variation in economic development. Although latitude may impact economic development, there are probably other more influential factors affecting it as well. Financial access in a country does not affect the latitude in the same way it could influence economic development, but latitude may impact financial access through economic development. Instead of using a dummy variable for countries in the tropics, we use the absolute value of the latitude of a country's midpoint to allow for variation depending on how far away from the equator a country is located.

If access to panel data were available, we would have encouraged using country and time fixed effects. Due to the shortage of available data on our dependent variable, this is not feasible. Instead, we introduce regional dummy variables in our models to capture any regional fixed effects. Countries in the same region may share social norms that could have a significant impact on our results. Because Abramova & Böhme (2016) argues that social norms may be of importance when deciding on whether or not to adopt bitcoin, we believe that it is sensible to try and capture this in some way.

The number of commercial bank branches per 100,000 people in 2017, from the International Monetary Fund (2017), is also included as a control variable. Although of diminishing importance today, it is still essential to take its historical impact on financial access into consideration, according to the World Bank (2012).

Finally, we introduce the share of the population that is Muslim in 2017 as a control to take into account possible differences across countries that may affect both financial access and the adoption rate. Islam is a source of large variation as its

³⁰For instance, the tropical zone is spanning the entire surface of the earth between 23.5 degrees North latitude and 23.5 degrees South latitude.

presence is known in many countries included in our dataset but differs a lot in terms of spread. It might also be the case that countries with a higher share of Muslims, on average, tend to have lower financial access, following the results by Ghosh (2020). Potential reasons for this are some particular properties of Islamic banking (e.g. the prohibition of interest on loans and deposits), outlined in a paper by Chong & Liu (2009). However, they do not find any solid evidence of such attributes in reality, at least not in Malaysia³¹. With a slightly different focus, Caporale & Helmi (2018) finds evidence of a relationship between Islamic banking and GDP growth in their paper³². Their finding is reinforced in a paper by Naz & Gulzar (2020). These papers illustrate the uncertainty of the real impact of Islamic banking in comparison to non-Islamic banking. Since we share the concern by Al-amri et al. (2019), that social norms may have a significant effect on the results when considering models for cryptocurrency adoption, a variable related to religion is included as it plays a role in shaping social norms. We focus on Islam partly because it provides more variation in our dataset compared to other, less widespread religions and partly because notable characteristics may be paramount in the formation of social norms, as suggested by Pakeeza & Chishti (2012). The potential impact of Islamic banking on financial access and possibly cryptocurrency adoption is another reason to include it as a control.

4.2 Identification

Using our dataset, we estimate the following OLS regression to capture the effect of financial access on CAR:

$$CAR_i = \beta_0 + \beta_1 AO_i + A_i'X + \epsilon \quad (4.1)$$

where CAR_i is the cryptocurrency adoption rate for country i , AO_i is the account ownership for country i , A_i is a vector of controls, and ϵ is an error term. In this regression, our coefficient of interest is β_1 , which indicates the effect of account ownership on CAR.

As claimed by Cunningham (2021), a concern when implementing a simple model like OLS is that the coefficient estimates may be biased. There are primarily three concerns why we believe that the OLS regression estimates potentially contain bias in our paper.

First, there may be variables critical to include as controls but are omitted from the model, either because there is no available data or because we have neglected it. Such variables should have an impact on both financial access and the adoption rate. Closely related to omitted variables bias is the potential issue of specification error. When running the link and the omitted variables tests, the null hypotheses that the model is specified correctly cannot be rejected. The idea is to create new

³¹They focus on Malaysia because it has the largest Islamic banking industry in the world. It is also a banking industry allowing both Islamic and non-Islamic banks to operate. To evaluate the relationship between interest rates in non-Islamic banks and Islamic banks, they run Granger causality, unit root, and cointegration tests. Since they find evidence of cointegration, they finally proceed with a cointegration based model.

³²They use a similar methodology (vector error correction model) as the Chong & Liu (2009) paper to determine the relationship but consider 14 countries, in which 7 have an existing Islamic banking industry.

variables based on the right-hand side variables included in the model specification and check whether they are significant or not. Our model can still be misspecified even if we fail to reject the null hypotheses of these specification tests because of the potential omitted variables that are not connected to the variables included in the model specification.

Some may consider GDP per capita as one example of an omitted variable. We showcase the results in Appendix A.3 (see Table A.11), where this variable is included in the models. However, we believe it is not appropriate to include GDP per capita as a control variable in our main regression framework as it can work as a mediator. State illegitimacy is another potential omitted variable. Again, the results from regressions are provided in Appendix A.3 (see Table A.13). For similar reasons, as GDP per capita could mediate the effect of financial access on CAR, we exclude it from our main regressions.

A more pertinent concern is that we expect bitcoin ATM density to influence the adoption rate and possibly the financial access. We cannot include any variable related to this potentially omitted variable in our models since there is no measurement for years before 2021. Because of the substantial heterogeneity within and between countries in bitcoin ATM functionality in terms of what they can do³³, it is possible that even if available data existed, it would probably have a limited impact, if any, on our results. Also, notice that there are few cryptocurrency ATMs offering access to altcoins³⁴.

One may be worried that the adoption rate of cryptocurrencies is related to the share of money participating in illicit activities within a country. However, when examining a report from Chainalysis (2021a), covering the use of cryptocurrencies in criminal activities, it is worth noting that only 0.34% of all cryptocurrency transactions are connected to criminal networks and illicit activities such as money laundering. Compared to fiat currencies, it is significantly lower, where the United Nations Office on Drugs and Crime (2011) have estimated the number to be in the region of 2-5%. By examining the regional and country analysis in Chainalysis (2021a), there are no indications that a large share of the illicit activities takes place in countries with high adoption rates. Considering the top ten countries where most illicit activities using cryptocurrencies materialise, most countries have low CAR values. Therefore, we would argue that the potential of cryptocurrencies in unlawful activities by criminal networks is not driving the adoption rate. If it was a significant factor, we should observe values greater, not lower, than those of fiat currencies. Consequently, we do not include any measure of the share of money participating in criminal activities in our models.

Second, as people start to adopt, own and use cryptocurrencies regularly, their access to financial services should increase, as they now have a way to save, access credit, or complete transactions. For instance, individuals can earn returns on their cryptocurrency holdings. Sergeenkov (2021) lists multiple ways of achieving this, including staking³⁵ and lending. The potential threat of reverse causality is an additional motive to implement an IV regression approach.

³³Examples of functionalities include the deposit and withdrawal of funds to a specific wallet, or sending transactions.

³⁴And in those cases, the offering is exclusively some of the top altcoins by market capitalisation.

³⁵It is a way of earning rewards by validating transactions on particular blockchains by locking up cryptocurrency on the network.

Third, as we use data collected by surveys, there is potential for measurement error, as explained in Angrist & Pischke (2009). It can occur in several steps of the data collection procedure, and some examples include recall or data coding errors. Suppose there are measurement errors in the financial access variable. In that case, our paper could experience what is known as attenuation bias³⁶. Both variables representing financial access could contain recall errors since it may be arduous to know whether one holds an account at a financial institution or has made a digital transaction in the past year. For CAR, some sampled units may have purchased cryptocurrency in past years and later forgotten that they still owned it. There is also a risk that some respondents falsely reported that they did not own any cryptocurrency because they did not trust the anonymity of the survey or had a lack of trust in the government. This event is more likely to occur in countries where governments hold an aggressive stance towards cryptocurrencies and may result in an underestimation of the adoption rate. We acknowledge these threats but do not want to overstate the scale at which they occur. Improving the data collection process can reduce the risk of measurement error. In addition, one could also run an IV regression instead of an OLS regression to reduce the impact from measurement error in the independent variables.

Instrument

Mobile financial services are a conceivable way of reaching financial inclusion. It is hard to ignore the impact smartphones have on financial access today. According to the U.S. Federal Reserve Board (2015), mobile phones have become an ordinary tool used to access bank accounts, complete online purchases and transfer money. Not only does it make online banking more accessible, but it can also make it easier to open a new bank account.

A research paper by Ouma (2017) investigates the impact of mobile financial services on financial access and savings in selected countries in sub-Saharan Africa. He concludes that in addition to saving more, using mobile financial services will also increase the probability of saving. Foremost, the technology and services provided by mobile phones and their accessible characteristics contribute to a positive change by reaching the unbanked part of the population. According to the Federal Deposit Insurance Corporation (2014), the unbanked are over-represented by less educated people, with lower income than the average population. Without smartphones, people might use non-bank financial services such as cash due to their convenience and speed to transact. It is therefore essential for banks to offer services that can facilitate customers' needs. Mobile financial services can help address this challenge by creating and sustaining a stronger bond between the bank and the customer and potentially help the unbanked to access services offered by the banking system.

A potential concern with our choice of instrument is the validity. We believe that smartphone penetration should affect the adoption rate exclusively by increasing the general level of financial access of a country's population. Some may disagree and argue that a third factor affects both the adoption rate and smartphone penetration or that there are some additional channels through which smartphone penetration may impact the adoption rate. Perhaps income, or other income-related factors, could

³⁶A case where estimated coefficients are closer to zero than the accurate values, which can cause the estimates to be insignificant.

affect smartphone penetration, account ownership and the adoption rate. However, there does not seem to be any clear evidence of such relationships on a global macro level. Focusing on the U.S. specifically, there seems to be a slight difference in mobile phone and smartphone penetration when comparing low-income to high-income Americans, according to Pew Research Center (2015), but not much research has been conducted within that field to investigate the relationship further. The differences are more distinct in the actual use of phones and other technologies (e.g. computers). In contrast, the historical explanation for the mobile phone revolution in Africa by Campbell-Verduyn (2018) might be an indication that this is not true when comparing low-income to high-income countries. Furthermore, James (2020) writes about the progression of smartphone adoption in developing countries that have taken place in recent years. In the early history of smartphones, when there were only expensive options on the market, a substantial share of people in developing countries could not afford a smartphone. They also had lower benefits of a purchase, as smartphones were produced for people in developed countries to be used in their everyday life. The introduction of cheaper alternatives, in combination with a greater focus on areas of application targeting people in developing countries, has led to an increased smartphone penetration rate.

According to Campbell-Verduyn (2018), a result of the growing mobile services is that financial access has increased rapidly in African countries after the mobile-money-revolution. Ouma (2017) states that mobile phones have resulted in more people starting to save and open bank accounts. Therefore, one could argue that smartphones contribute to financial access by increasing the possibilities for the unbanked to begin saving and opening new accounts at financial institutions. Because of this, we believe that smartphone penetration is a relevant instrument for financial access. To measure it, we use the report by Newzoo (2017), containing information on the share of the population that are using smartphones.

4.3 Method and Model Specification

To avoid biased results from running OLS regressions, we prefer an instrumental variables approach to single out how financial access affects the adoption rate. Given that the assumption of a valid instrument holds, this method increases the probability that our paper captures the causal effect on compliers. The instrumental variables method consists of three models. These are the first-stage, the second-stage, and the reduced-form. In our paper, they look like the following:

$$AO_i = a_0 + a_1 SP_i + A_i' \gamma + e \quad (4.2)$$

$$CAR_i = b_0 + b_1 \hat{AO}_i + A_i' \phi + u \quad (4.3)$$

$$CAR_i = c_0 + c_1 SP_i + A_i' \lambda + v \quad (4.4)$$

where SP_i is the smartphone penetration in country i , and e , u and v are error terms. The first-stage regression, given by Equation 4.2, tests whether the instrument (SP) has a significant effect on the endogenous variable (AO). In this regression, a_1 is the primary coefficient of interest. It indicates the influence of

smartphone penetration on account ownership. If significant, the instrument fulfils the relevance condition as specified by Angrist & Pischke (2009). We believe that there should be a positive relationship because a higher smartphone penetration rate should increase access to financial services, as argued by the Federal Reserve Board (2015) and Burhouse et al. (2014). As stated by Bound et al. (1995), it is crucial that the instrument and the endogenous variable showcase a high correlation to reduce the bias since we are working in a finite sample with a relatively small sample size. The second-stage regression, given by Equation 4.3, use the predicted values of the endogenous variable (AO) from the first-stage regression to calculate its effect on the dependent variable (CAR). Here, b_1 is the main coefficient of interest, indicating the influence of account ownership, predicted by the first-stage regression, on CAR. Finally, in the reduced-form regression, given by Equation 4.4, we retrieve an estimate of the effect of the instrument (SP) on the dependent variable (CAR). In this regression, the predominant coefficient of interest is c_1 , indicating the effect of smartphone penetration on CAR.

As suggested by Cunningham (2021), robust standard errors are used since the assumption of homoskedasticity is unrealistic in most settings. When examining this assumption by plotting residuals against fitted CAR values, there are signs of heteroskedasticity as the variance seems to be higher for increasing values of fitted CAR values in Figure 4.2. Also, when running a White's test, the null hypothesis of homoskedasticity is rejected (with a p-value of 0.0211). The outcome is confirmed by a Breusch-Pagan test, also indicating rejection of the null hypothesis of constant variance of the residuals (with a p-value of 0.0000).

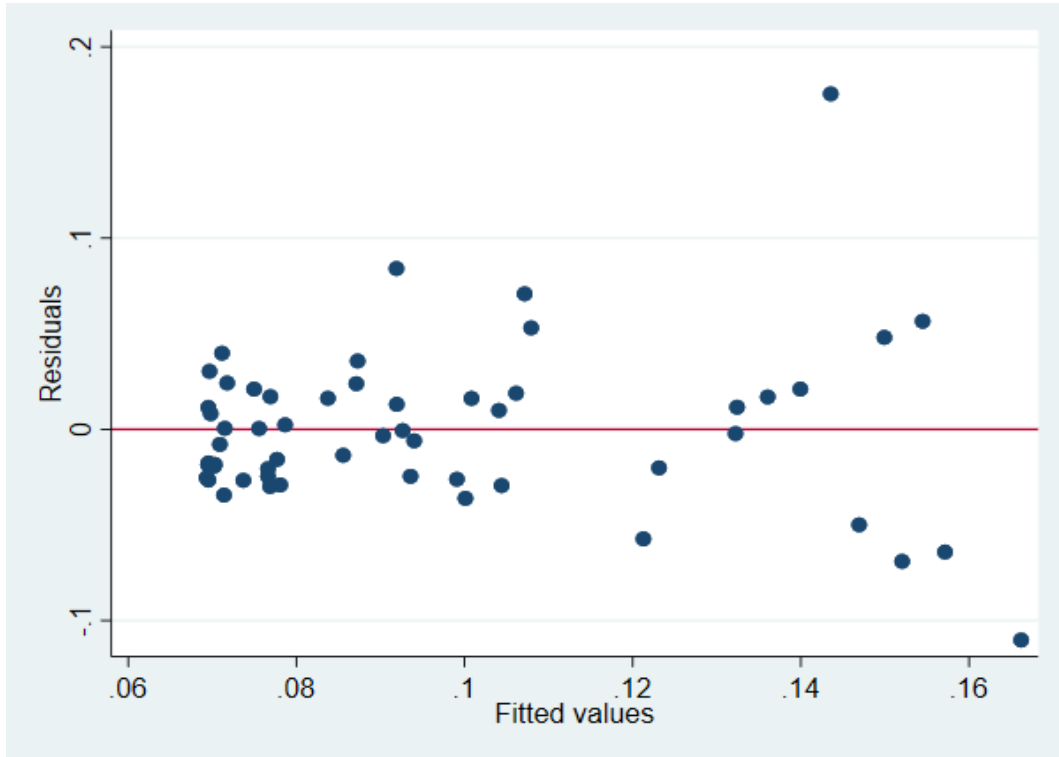


Figure 4.2: Scatter plot of residuals against fitted CAR values.

Furthermore, a linear probability model is used instead of any non-linear probability model when running the above regressions. There are some advantages of

doing so by words of Aldrich & Nelson (1984). For instance, the estimations and interpretations of the parameter estimate are more straightforward than non-linear methods. Still, there are some shortcomings of using linear probability models. For example, extrapolating the result beyond what is covered by our observations in our sample might suggest that it is possible to reach an adoption rate higher than 100%, or even a negative CAR. This is impossible in reality, and why some would instead suggest using non-linear probability models, which are bounded by 0 and 1.

To evaluate the importance of the variables included on the right-hand side of the equations listed above, we also provide standardised regression outputs in Appendix A.3 (see Table A.3, A.4, and A.6). To standardise the continuous variables included in our model, we subtract a variable's mean from every observation and divide the result by the standard deviation. The procedure is given below by Equation 4.5:

$$S_{ia} = \frac{x_{ia} - \bar{x}_a}{z_a} \quad (4.5)$$

where S_{ia} is the standardised value of an observation i for variable a . x_{ia} is the original value for observation i and variable a , $\bar{x}_a$ is the mean of variable a , and z_a is the standard deviation of variable a .

5. Results

5.1 Cryptocurrency Adoption Rate

In Table 5.1, the results of the first-stage regression are presented. We formally prove the relevance of the instrument by the relatively high F-statistic³⁷ of 41.399, shown in Table 5.1. The fulfilment of the relevance condition is strengthened by the strong correlation (0.8196) between smartphone penetration and account ownership in our sample. From Table 5.1, one can also notice that the coefficient estimate for smartphone penetration is positive and significant on the 0.1% significance level. A one percentage point increase in smartphone penetration increases account ownership by 0.899 percentage points on average, holding all other variables fixed. From Table 5.2, the null hypothesis is rejected that smartphone penetration is redundant at a 1% significance level when conducting a Lagrange multiplier redundancy rank test.

³⁷In general, it requires an F-statistic over 10 in order to classify the instrument as sufficiently strong.

Table 5.1: Account Ownership: First-stage Regression Output

	(1) Account Ownership
Smartphone Penetration	0.899*** (0.140)
Bank Branches	-0.000 (0.001)
Muslims	-0.212** (0.072)
Latitude	-0.013 (0.100)
Constant	0.338* (0.132)
Regional Controls	YES
Observations	55
Kleibergen-Paap's F-statistic	41.399

Robust standard errors in brackets.

First-stage regression output showing the relationship between smartphone penetration and financial access, measured using account ownership.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.2: Lagrange Multiplier Redundancy Rank Test

	Value
Test statistic	11.524
P-value	0.0007

The table presents the output from a redundancy rank test to check whether the instrument is redundant. The test statistic follows a χ^2 distribution with 1 degree of freedom since we have one instrument and one endogenous variable.

The result from the main OLS and IV regression, using CAR as the dependent variable, is given in Table 5.3. In both regressions, the coefficient estimate of account ownership is significant at the 5% significance level with a negative impact on CAR, indicating that an increase in account ownership tend to decrease CAR. More specifically, looking at the OLS estimate, an increase of 1 percentage point in account ownership will, on average, holding all other variables in the model fixed, result in a 0.079 percentage point decrease in CAR. For the IV estimate, the interpretation is the same, but a one percentage point increase in account ownership would lead to a 0.088 percentage point decrease in CAR. Furthermore, latitude also has a negative impact on CAR. It is significant at the 1% significance level, indicating that living a degree further away from the equator decreases CAR by 0.098 percentage points (IV estimate) on average, holding all other variables fixed. The remaining coefficients for the control variables yield negative but insignificant estimates.

Table 5.3: CAR: OLS and IV Regression Output

	(1)	(2)
	CAR	CAR
Account Ownership	-0.079*	-0.088*
	(0.038)	(0.041)
Bank Branches	-0.000	-0.000
	(0.000)	(0.000)
Muslims	-0.025	-0.027
	(0.029)	(0.026)
Latitude	-0.100**	-0.098**
	(0.034)	(0.030)
Constant	0.231***	0.238***
	(0.038)	(0.040)
Regional Controls	YES	YES
Observations	55	55

Robust standard errors in brackets.

Regression outputs using CAR from Statista. In column 1, the OLS regression estimates are provided. In column 2, we present the IV regression estimates.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.4 provides measures of multicollinearity. Column 1 presents the variance inflation factor (VIF), and column 2 presents the tolerance. Based on the output, our model does not seem to have any issue with multicollinearity³⁸. The VIF-scores are low, ranging between 1.05-2.95. These scores are well below 10. The tolerance scores (the inverse of VIF) range between 0.34-0.95. These values also indicate that our model does not have an issue with multicollinearity³⁹.

Table 5.4: Measures of Multicollinearity

(1) Variable	(2) VIF	(3) Tolerance
Latitude	2.95	0.340
Asia	2.86	0.350
Africa	2.04	0.489
South America	1.98	0.505
Financial Access	1.96	0.510
Muslims	1.64	0.609
North America	1.33	0.753
Oceania	1.17	0.857
Bank Branches	1.05	0.950

Multicollinearity check for the primary OLS regression, providing statistics on the variance inflation factor and the tolerance. The variables are listed from highest to lowest in terms of their VIF-score.

To achieve more robust findings, we present in Table 5.5 and 5.6 the result when using digital transactions instead of account ownership. The results from the first-stage regression are presented in Table 5.5. A one percentage point increase in smartphone penetration increases digital transactions by 1.161 percentage points on average, holding all other variables fixed, and is significant at a 0.1% significance level. The instrument is also relevant as the first-stage F-statistic, in this case, is higher than the previous case at 85.164, and the correlation is 0.9420.

³⁸As a rule of thumb, a VIF-score above 10 indicates multicollinearity

³⁹As a rule of thumb, a tolerance score below 0.1 indicates multicollinearity

Table 5.5: Digital Transactions: First-stage Regression Output

	(1) Digital Transactions
Smartphone Penetration	1.161*** (0.126)
Bank Branches	0.002 (0.001)
Muslims	-0.185 (0.093)
Latitude	0.078 (0.145)
Constant	-0.056 (0.145)
Regional Controls	YES
Observations	55
Kleibergen-Paap's F-statistic	85.164

Robust standard errors in brackets.

First-stage regression showing the relationship between smartphone penetration and financial access, measured using digital transactions, with coefficient estimates reported in column 1.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.6 provide the output, using digital transactions, where the OLS regression is presented in column 1 and the IV regression in column 2. Similar to the results given in Table 5.3, the latitude coefficient estimate is again significant at the 1% significance level with a similar magnitude. However, the magnitude of the digital transactions coefficient estimate is now lower than when account ownership was used as the endogenous variable. For the IV regression, it is significant at the 5% significance level.

Table 5.6: CAR: OLS and IV Regression Output

	(1)	(2)
	CAR	CAR
Digital Transactions	-0.058 (0.030)	-0.068* (0.032)
Bank Branches	0.000 (0.000)	0.000 (0.000)
Muslims	-0.018 (0.028)	-0.021 (0.026)
Latitude	-0.095** (0.035)	-0.091** (0.029)
Constant	0.200*** (0.030)	0.204*** (0.031)
Regional Controls	YES	YES
Observations	55	55

Robust standard errors in brackets.

Regression outputs using CAR from Statista and digital transactions as financial access variable. In column 1, the OLS regression estimates are provided. In column 2, the IV regression estimates are provided.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Cryptocurrency Adoption Index and Bitcoin Trading Volume

Different metrics are used to measure the adoption rate to strengthen the reliability of the relationship between financial access and the adoption rate. These results are provided in Table 5.7. In column 1, CAI is used as the dependent variable, and in column 2, the dependent variable is BTV. Again, the account ownership coefficient estimate is significant at the 5% significance level in both cases. Using CAI, the relationship is negative, similar to the result using CAR. Furthermore, our control variable Muslims is significant at the 1% significance level with a negative impact on CAI. In the case of BTV, account ownership instead has a positive impact. In this case, bank branches is significant at the 5% significance level. However, for this output, it is essential to note that the number of observations is fewer.

Table 5.7: CAI and BTV: IV Regression Output

	(1) CAI	(2) BTV
Account Ownership	-0.411* (0.186)	1.789* (0.766)
Bank Branches	0.001 (0.001)	0.015* (0.007)
Muslims	-0.317** (0.099)	-0.029 (0.322)
Latitude	0.081 (0.170)	-0.426 (0.629)
Constant	0.445** (0.173)	-0.522 (0.962)
Regional Controls	YES	YES
Observations	54	36

Robust standard errors in brackets.

IV regression outputs for the dependent variables from Chainalysis and Statista. Column 1 provides the IV estimates using CAI from Chainalysis as dependent variable. Column 2 provides the IV estimates using BTV as dependent variable.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Comparison of Dependent Variables

Based on our results in the previous subsections, we believe that a deeper analysis of the variables CAR and CAI is necessary to evaluate whether or not they are similar. To accomplish this, we provide descriptive statistics, correlation measures, and scatter plots. BTV is not included in the comparison because the regression results indicate that it is not a similar measure and should showcase a negative correlation with CAR and CAI.

In Table 5.8, some descriptive statistics are provided for CAR and CAI (excluding Taiwan). Some apparent differences can be noted. CAI's mean value (provided in column 2) is more than twice as large as CAR's. However, there is an even more significant difference when considering the maximum value, which is almost three times as large for CAI, compared to CAR. The standard deviation for CAI is also almost four times larger than CAR. Only the minimum values have a similar magnitude.

Table 5.8: Descriptive Statistics for CAR and CAI

(1) Variable	(2) No. Obs	(3) Mean	(4) Min	(5) Max	(6) Std
CAR	54	0.098	0.037	0.319	0.051
CAI	54	0.213	0.033	0.931	0.190

Descriptive statistics for CAR and CAI, excluding Taiwan. Provided are the mean value, the lowest and highest value, and the standard deviation.

Continuing with a visual inspection of the data, a scatter plot of the two datasets is provided in Figure 5.1. First, one should note that most observations lie within 0.2 for both variables. This indicates that the adoption level is low in most countries. Second, as CAI increases, the variation in CAR increases. Third, the four observations scoring highest on CAI (Russia, China, Kenya, and the United States) have a score that is more than five times greater than the corresponding CAR. We consider these observations to be extreme cases. Together, these findings imply that as CAI increases, the connection to CAR is lost.

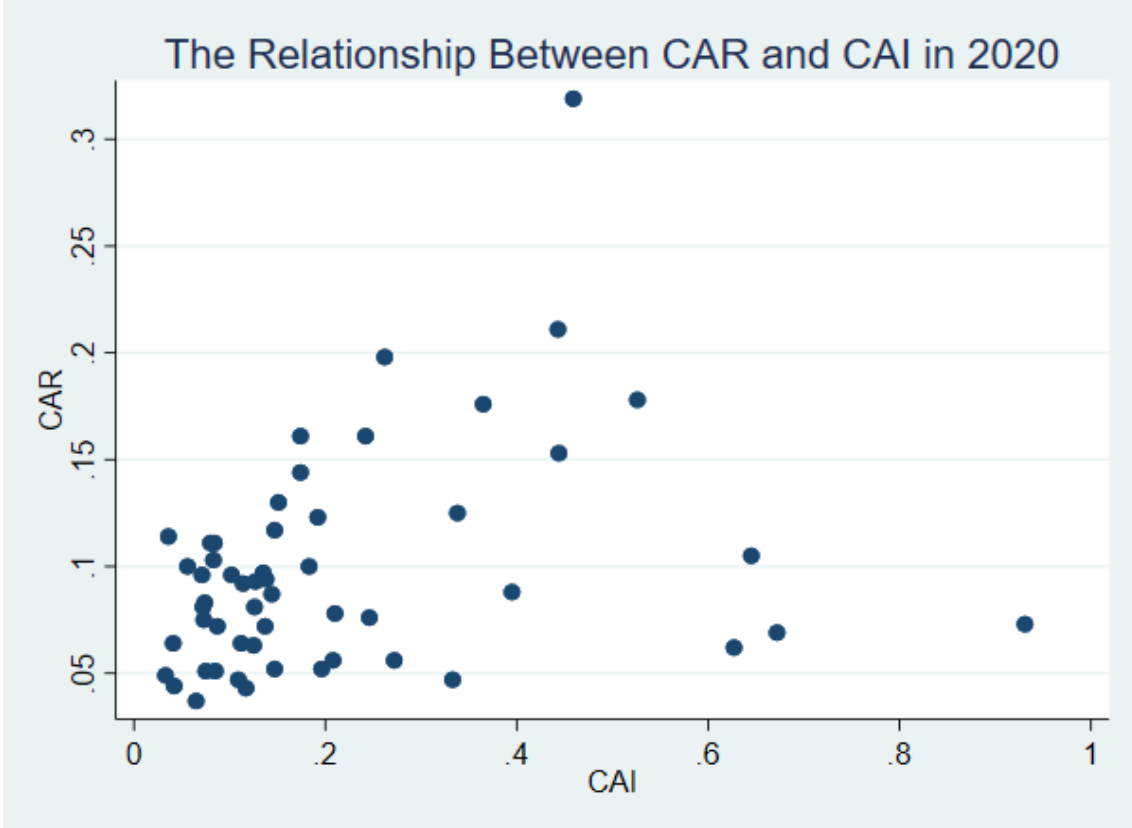


Figure 5.1: Scatter plot of CAR against CAI.

From Figure 5.1, we note that as CAI increases, the linear relationship to CAR diminishes. It can be more easily seen by looking at Figure 5.2, where the four extreme observations have been excluded. In a sense, it is challenging to decide on a rule of which observations should be considered outliers in our datasets. CAR and CAI are separate metrics based on different estimation methods, and it may be difficult to visually or numerically decide when the connection between CAR and CAI is lost. We decide to exclude those observations that score above 0.5 in CAI and have a CAI-score five times greater than their corresponding CAR-value because these observations do not seem to follow the same relationship as the others. It implies that we do not believe that CAR and CAI are similar for values outside this range.

Continuing, the similarities between CAR and CAI, when excluding the four extreme observations, are given in Figure 5.2. There seems to exist some positive linear relationship. However, it is difficult to determine how strong this relationship is and whether a non-linear relationship is more suitable than a linear one.

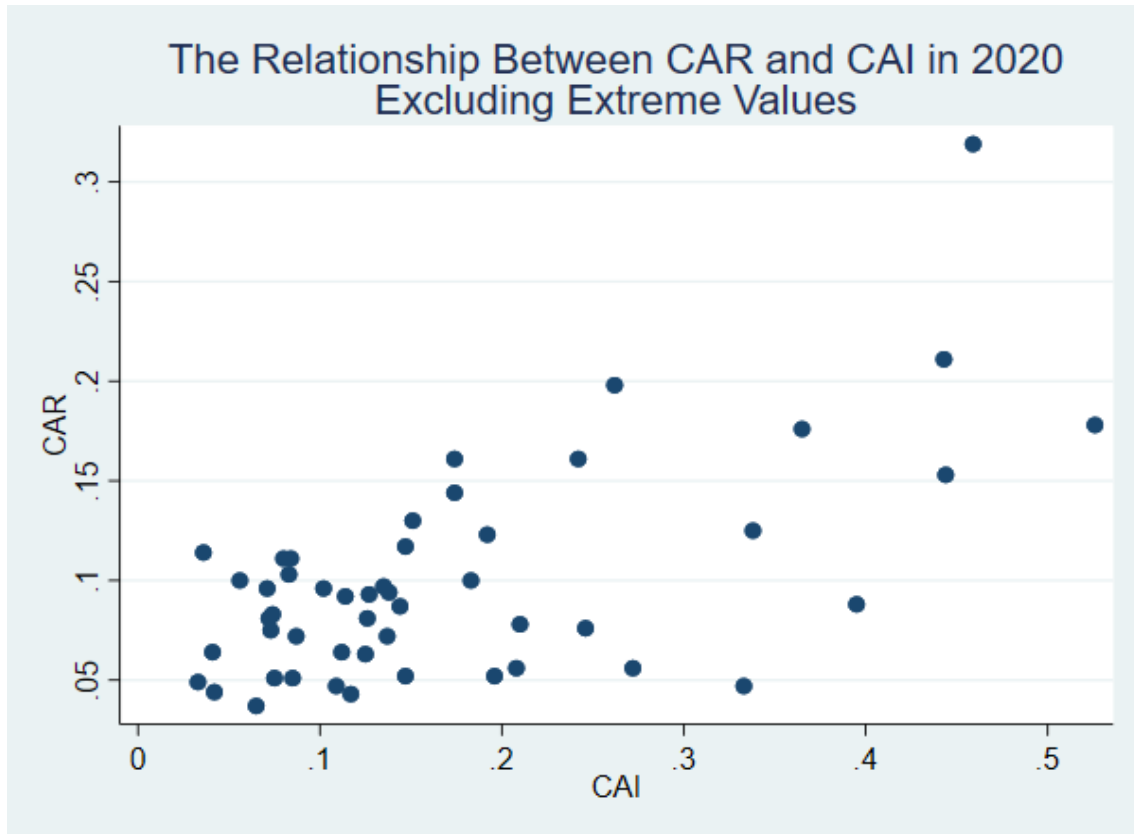


Figure 5.2: Scatter plot of CAR against CAI, excluding extreme values.

Measures of correlation between the two datasets are provided in Table 5.9 using different sample sizes. One could notice that excluding potential outliers results in the correlation going from 0.3 to 0.63. For observations with lower values on CAI, there seems to exist some positive linear relationship between the two metrics. This relationship diminishes as extreme observations are included in the sample.

Table 5.9: Correlation Between CAR and CAI

Number of Observations	Correlation
54	0.30
53	0.39
50	0.63

Correlation between CAR and CAI data. The first row provides the correlation for the full dataset (excluding Taiwan as it is not measured in CAI). In the second row, the correlation is measured for the dataset, excluding the most extreme value of Russia. The third row excludes other potential outliers (United States, China, and Kenya).

6. Discussion

6.1 Discussion of Results

Based on the output in Table 5.3 and the first column in Table 5.7, it is clear that using CAR or CAI yields similar results. For both dependent variables, the coefficient on financial access is negative and significant. Albeit difficult to interpret the economic similarities due to the differences in estimating the adoption rate of cryptocurrencies, this finding may suggest that it is possible to measure the adoption rate using either survey methods or on-chain transactions and trading volumes. Obviously, this holds for 2020 and does not change if excluding Taiwan from the Statista (2020b) data, but it should probably be investigated further when more data is available. For our datasets, we have found that financial access has a negative impact on CAR. When it is measured using account ownership, the estimated coefficient is approximately -0.088, and when it is measured as digital transactions, the estimated coefficient is approximately -0.068. Although the impact is slightly smaller when using digital transactions, both measures indicate an impact on CAR in the same direction. This result is also supported when focusing on CAI. In all IV regressions, the leading coefficient of interest is significant at the 5% significance level. Hence, we conclude that the first hypothesis in our paper holds. Increasing financial access negatively impacts the cryptocurrency adoption rate.

This finding highlights something important. By increasing the financial access of its citizens, an executive authority can reduce the adoption rate of cryptocurrencies, at least considering countries within our range of data on CAR (0-32%). For some regimes, it could be a fundamental goal to strengthen the importance of their domestic fiat currencies to remove any digital or foreign alternatives threatening their existence. With the coefficient estimates indicating a decrease by about one-tenth percentage point in CAR for a percentage point increase in financial access, the effect is sizeable but should not be exaggerated. Other alternative efforts may have a more distinct impact on reducing the ownership and use of cryptocurrencies. However, as Pandya et al. (2019) have suggested that outlawing cryptocurrencies have a limited effect, it can be challenging to find such alternatives. Suppose that the authorities are embracing cryptocurrencies instead of considering them as a threat. Under these circumstances, it may not be worthwhile to exert effort to increase financial access for the sole sake of safeguarding their local currencies.

The differences in magnitude when using CAR and CAI is probably due to the underlying differences in the metrics. In general, the data from Chainalysis (2020) has higher values since the base of the index is the top-scoring country, given a score of 1, and other countries were given a relative score between 0 and 1. In contrast, the data from Statista (2020b) use a base score of 0 and provides countries with

a score between 0 and 1 based on actual cryptocurrency adoption. The difficulty in interpreting coefficients using CAI, in combination with the fact that it may not capture the adoption rate, but something strongly correlated (e.g. average transaction value per capita), provide us with a reason to prefer CAR over CAI. It should be noted that having more observations, 139 compared to 55 when working on a small sample as we do, is a compelling reason to use the larger dataset if they provide similar outcomes. This, however, builds on the assumption that the results would be similar for countries not included in the dataset. With some regions being more represented than others in our dataset, this could significantly impact our findings. As time pass, more data will become available from both data sources, providing future researchers with more possibilities to select a suitable method to investigate the relationship between financial access and the adoption rate. Having data on more years will increase the sample size, estimates will become more precise, and allow for an opportunity to use panel data methods.

With the finding of CAR and CAI having a strong correlation when excluding observations obtaining CAI-values above 0.5 and five times greater than the corresponding CAR, the measurements seem to be similar when considering lower adoption rates. In contrast, for higher adoption rates, the datasets are not remarkably similar. We believe that this outcome is primarily driven by underlying differences in methods and country-specific characteristics. Nevertheless, a word of caution is necessary. It is possible to achieve a higher correlation by removing observations, but this should be practised with caution. After all, the final dataset may no longer represent the underlying data, and the implications of any results after arbitrarily removing observations are unusable. CAI is a relative measurement of adoption, whereas CAR is an absolute measurement of adoption. This difference could negatively affect the correlation, as the relationship may not be linear. Still, this finding can allow some researchers to, in some cases, use the larger dataset on CAI by only considering countries with lower cryptocurrency adoption. However, for studies including countries with higher adoption rates, we encourage using the dataset on CAR.

It is also interesting to delve deeper into the four excluded countries and analyse why they significantly impact the correlation measure. Some of the countries share specific characteristics. For instance, cryptocurrencies were considered illegal in China and Russia during the data collection period, according to Gong & Yu (2019) and Strizh et al. (2019). Although the specific legality status differed between the countries, this shared characteristic could affect how individuals report their ownership of cryptocurrencies in surveys in fear of their authoritarian regimes and influential leaders. CAR could therefore underestimate the actual adoption rate in those countries because individuals may fear severe punishment if detected. Despite this, other countries have similar features in our dataset, so it does not thoroughly explain the differences between CAR and CAI. Common characteristics shared by China, Russia, and the United States that could affect CAI being different from CAR are that they all have large populations and a high GDP, but this is also true for other countries in the dataset. On a global level, their domestic fiat currencies are also relatively important when considering trading volumes. Even though the U.S. dollar is the most critical fiat currency, the Euro and the Yen are two examples of frequently used fiat currencies in countries with a lower reported CAI. Despite the difficulty to pinpoint why these three countries specifically stand

out when comparing CAR and CAI, some potential features and characteristics may provide part of an answer. In the case of Kenya, we cannot identify specific factors that separate the country from the others. Perhaps there is something related to the fact that the mobile money revolution started in Kenya, according to Campbell-Verduyn (2018), that yields the discrepancies in CAR and CAI. One example could then be technological innovation.

Interestingly, using bitcoin trading volume per capita as a dependent variable yields a positive coefficient estimate for the financial access variable, in stark contrast to using the other two dependent variables. From the second column in Table 5.7, the main coefficient of interest is estimated to be 1.789 and is significant at the 5% significance level. Hence, we conclude that the second hypothesis in our paper holds, that increased financial access positively impacts the bitcoin adoption rate.

There are differences when using BTV as a dependent variable instead of CAR or CAI. While the other dependent variables focus on cryptocurrencies in general, bitcoin trading volume per capita only considers one of the thousands of existing cryptocurrencies. Although Chainalysis (2020) also considers trading volume when computing CAI, there are two significant differences between the two metrics. The more obvious one is again the fact that Chainalysis (2020) considers cryptocurrencies in general in their trading volume metric, and not bitcoin specifically. However, they also include measurements of deposits and transfers of cryptocurrencies. Therefore, one could argue that bitcoin trading volume per capita may not capture the general BAR but instead be more prone to capture investors buying bitcoin as a speculative asset only (a subset of BAR). Suppose there was an index for bitcoin, similar to CAI from Chainalysis (2020), considering deposits and transfers, in addition to trading volume in bitcoin. Then it might have been a better proxy for BAR, capturing more of the on-chain activity. It is difficult to know whether this would change the outcome since there could still be a big enough difference when considering bitcoin only, compared to cryptocurrencies in general. Consequently, the positive relationship between financial access and BAR may persist. It can also be the case that including additional aspects such as deposits and transfers could cause the relationship to turn negative. Another potential explanation for BTV showcasing a positive relationship is the difference in the number of observations. When using CAR and CAI, the sample size is almost increased by 20 observations compared to BTV. Even though there is still a spread in countries from different regions, this could partly explain the difference in sign.

A suggestion by Alzahrani & Daim (2019) is to use the number of unique wallet addresses as a measure of the adoption rate. They realise, however, that it would not accurately capture the adoption rate, as there is no limit on the number of unique wallets a single user can create, own and use, which is explained by Rauchs & Hileman (2017)⁴⁰. In addition, this metric would not allow us to explore differences on a country-level as nothing is connecting the creation, use or ownership of a wallet address to a specific citizen of a country. A better alternative would be to use the number of cryptocurrency exchange users per country or region, but a single user has the potential to open accounts on several exchanges. There is also an obvious risk that any cryptocurrency exchange in a specific country is unwilling

⁴⁰They estimate that there were 101 million users in 2020, but a total of 191 million accounts. These numbers include companies and financial institutions, where about 70% of the user base consists of consumers, with some differences across regions.

to provide a researcher with such data. Thus, we believe that the best way to measure the adoption rate is by sample survey. It is also the most commonly used method in previous literature, although most studies focusing on the adoption rate usually focus on sub-populations in specific countries and have an issue with few observations. Related to this is a sample survey study by Abbasi et al. (2021), focusing on Malaysia. Even though the data we use is also based on a small sample, with 55 countries considered⁴¹, the individual country estimates have many elements and provide reliable estimates for the CAR of every single country in our dataset.

Based on our results, we conclude that using bitcoin trading volume per capita as a proxy for CAR seems unreasonable. However, the estimates retrieved from column 2 in Table 5.7 are still interesting as they still provide important insights regarding the effect of financial access on bitcoin trading volume per capita. In contrast to cryptocurrencies in general, our finding suggests that bitcoin cannot be contested by governmental strives to increase financial access as this would increase the ownership and use of bitcoin. Therefore other approaches are necessary. Similar to previous studies by Glaser et al. (2014), Baur et al. (2017), and Cheah & Fry (2015), we find that bitcoin can be viewed as a speculative asset. As opposed to these studies focusing on price action, we have focused on trading volumes. However, we do not make any further claims regarding the usefulness and value of bitcoin outside this context. Instead, we ask for more data collection on other bitcoin-related metrics resulting in creating a BAR-index, similar to CAI, that could be used to explore this further.

By examining the result in our principal regression provided in Table 5.3, it is clear that the estimated magnitude of a change in the main coefficient of interest (financial access) on CAR is greater in the IV regression compared to the OLS regression. A potential reason for this outcome is that measurement error exists in the endogenous variable, resulting in attenuation bias of our OLS estimate towards zero. Similar results are given when using bitcoin trading volume as the dependent variable, with higher estimates for the coefficients of interest in the IV regression than the OLS regression. When considering the coefficient of interest using CAI as the dependent variable, the indications of attenuation bias are even more substantial. This finding suggests that it may be challenging to measure financial access and stress the importance of using an instrumental variables approach to capture the causal effect of financial access on the adoption rate. Similar results are given when using digital transactions instead of account ownership as the endogenous variable. The magnitude of the digital transactions coefficient is also higher in the IV regressions, compared to OLS regressions, given in Table 5.6.

Related to this is the two different ways of measuring financial access. In theory, the former metric captures a broader range of the financial access concept, whereas the latter focuses more on the increasingly important vertical of completing transactions. By comparing our results in Table 5.1 and Table 5.5, one could see that the F-statistic in the first-stage regression is higher when using digital transactions (85.164) than account ownership (41.399). When comparing the coefficient estimate of interest, smartphone penetration has a positive estimate that is statistically significant at a 0.1% significance level for both ways of measuring financial access. Together, these findings imply that smartphone penetration is a relevant instrument no matter which metric we use to measure financial access. Still, the

⁴¹Which is still more than many of the previous studies considered.

higher F-statistic indicates that the first-stage relationship is stronger for digital transactions. Any violation of the exclusion restriction, although detrimental, will therefore have a lower impact on the results using this metric. We further notice by comparing Table 5.3 and 5.6, that the coefficient estimates of interest are slightly lower when using digital transactions compared to account ownership.

Another interesting difference is that the control variable capturing the effect of the share of Muslims in a country is significant only when considering regressions using account ownership as the endogenous variable. It is reasonable because saving or borrowing fiat currency from a financial institution or mobile financial service is more of a choice that might be affected by an individual's beliefs and values, whereas completing transactions is more of a necessity in a society. Of course, there is a difference between completing and having access to digital transactions.

6.2 Connection to Theory and Research

When comparing our results to the existing literature, we find several similarities. When using CAR and CAI, a negative statistically significant relationship is found for the financial access variables, indicating that individuals in countries with lower financial access seem to have more substantial incentives to own and use cryptocurrencies. It falls in line with the propositions in the papers by Pandya et al. (2019), Nadeem et al. (2021) and Campbell-Verduyn (2018), suggesting that unbanked people in societies with high cash usage and big shadow economies should be more open to adopt and use cryptocurrencies. The same goes for individuals working far away from their families and that are frequently completing cross-border transactions.

Additionally, the fact that the relationship is positive when considering bitcoin may indicate that Glaser et al. (2014), Baur et al. (2017), and Cheah & Fry (2015) were correct as well in their findings of bitcoin only working as a speculative asset to the benefit of people in countries with higher financial access. This might strike as a contradiction for some. How can financial access negatively affect the adoption of cryptocurrencies when it has a positive relationship with bitcoin adoption? While answering this, it is essential to remember that over ten thousand cryptocurrencies have been created with different intentions. Although bitcoin is by far the most prominent cryptocurrency, it is also the first cryptocurrency. Since its inception, new cryptocurrencies have been created to offer even faster and cheaper transactions. An example of this is the cryptocurrency XRP, and the interested reader should consult the whitepaper by Schwartz et al. (2014). By comparing this whitepaper to that of Nakamoto (2008) on Bitcoin, one will find many differences between the two cryptocurrencies. Hence, particular cryptocurrencies (e.g. bitcoin) can benefit the West, whereas others can benefit the rest.

6.3 Limitations and Considerations

Even if cryptocurrencies have gained attention over the past years, it is still a relatively new area that has not been studied and explored to a large extent. As a result, it has therefore not been easy to find available data and previous research papers that could support our results. There are some limitations to our data that should be highlighted. First, the sample of the data on CAR, published by Statista

(2020b), only includes 55 countries. It was, however, the best available data on the adoption rate that we found. After all, one should observe that the limitation of having a small sample may cause the coefficient estimates from the regressions to be insignificant, which does not have to be fully representative of the reality. Second, the data is only collected from one period of time. There might have been a particular event in that specific year that caused CAR to either increase or decrease. If data from more periods were available, that would also have been a source of variation that could contribute to more precise and reliable results.

In section 4, we provided information on countries included in the CAR dataset, and it should be clear that some regions are more represented than others. Specifically, we noticed that few African countries were included. It is uncertain in what direction our results would be affected if more African countries were included if affected at all. From Figure 4.1, it is clear that some of the countries with the highest tendency to adopt cryptocurrencies were African. Especially Sub-Saharan African countries seem to have a high CAR. Nigeria and South Africa were among the wealthiest African countries in 2017 in terms of raw economic development statistics, such as GDP. However, when comparing GDP per capita, they were not as highly ranked due to their large populations. Still, both of these countries could be considered more prosperous than most African countries. It is possible that for excluded countries, the underlying characteristics and the adoption of cryptocurrencies are somewhat different from the countries included in our sample. We also noticed that no Central Asian country was included in our dataset. Although some parts of China, India, and Pakistan is considered to be geographically located in Central Asia, the major parts of these countries are not. Therefore, it seems unreasonable to assume that the CAR in Central Asian countries would be resembling the CAR for China, India, or Pakistan in total. Based on the report from Hileman (2015), all of the Central Asian countries seems to have a high potential use of bitcoin. If we believe that this would indicate that they would, similar to Nigeria and South Africa, have a high cryptocurrency adoption rate, it would most likely strengthen our results by including those countries as they also tend to have relatively low financial access. When using CAI, we were able to include more African and Central Asian countries in our regressions, and the output still suggests a significant relationship between account ownership and CAI (see Table A.9 in Appendix A.4). The magnitude of the coefficient of interest was even more negative, suggesting a stronger impact from changes in financial access. Therefore, we believe that it is possible that including more African and Central Asian countries would strengthen our findings. Nonetheless, there is a need for more data collection on CAR in more countries for greater external validity.

Another limitation, which is identified by Abramova & Böhme (2016), is the difficulty of finding previous literature focusing on bitcoin in the traditional way of using databases and journals. Not only is it a topic that spans multiple research fields, but they also argue that some of the most prominent papers were not included in databases that are commonly used. After exploration, we have experienced something similar first-hand. Although our focus in terms of aims and research questions are slightly different, we would add that not much has been done in general, and the papers are of varying quality.

6.4 Directions for Future Research

When including income-related variables in our regressions, there are still significant relationships between account ownership and CAR. The first-stage regression also continues to indicate that smartphone is a relevant instrument for account ownership. This is shown in Table A.10 and A.11 in Appendix A.5, where GDP per capita in the year 2017 is included. It does result in slightly higher VIF-values when including it in regressions with controls. A likely explanation, however, is that latitude should affect income-related variables as proposed by previous literature. It should be clear that because financial access might affect the adoption rate partially through its positive effect on income, we decided not to include income-related variables in our models as it would mediate the effect. Instead, we use the fact that latitude, by construction, is not affected by financial access and include it as a control variable. By doing so, some effect of income that is not due to differences in financial access can be captured. Despite that, we suggest that future research investigates the relationship between income and smartphone penetration across countries globally and, if a relationship is found, decide its direction of impact and magnitude. We also encourage other ideas on potential instruments that could be used instead of smartphone penetration.

In addition, Alzahrani & Daim (2019) suggested that state illegitimacy may be an essential factor in determining the adoption rate. Therefore it would be interesting to investigate its effect using cross-country data and discover whether this relationship holds on a macro level or differ from country to country. As it may be challenging to find an instrument that could be used and based on the current data situation, we remain cautious of exploring this idea further in the near future.

7. Conclusion

In our paper, smartphone penetration is used as an instrument to investigate the effect of financial access on the cryptocurrency adoption rate. We show a strong first-stage relationship between smartphone penetration and both measures of the endogenous variable (account ownership and digital transactions). Financial access is influential in determining the cryptocurrency adoption rate on a global level using IV regressions. In line with our proposed hypothesis, an increase in financial access has a negative effect on the adoption rate. It holds for all combinations of the endogenous and the dependent variables related to cryptocurrencies in general.

Focusing on bitcoin specifically, we find that financial access is an influential variable in determining the bitcoin adoption rate. In contrast to CAR or CAI as dependent variables, its effect is positive when using BTV. Consequently, evidence in favour of the second proposed hypothesis is found. The differences highlights the need for an authority seeking to strengthen the importance of a domestic currency to proceed with different approaches to combat bitcoin specifically and cryptocurrencies

in general. By increasing financial access, one may reduce the adoption of some cryptocurrencies used for cross-border transactions but increase the adoption rate of cryptocurrencies used for investment purposes. Since our hypotheses are based on existing literature, finding evidence for both indicates that our findings are in line with current research within the area.

By examining the two competing methods of computing the adoption rate of cryptocurrencies, our paper has explored a survey-based absolute measure versus a quantitative-based relative index measure. The two methods are similar when considering countries with lower adoption levels but not countries with higher index values. We propose two explanations for the differences. It may be that country-specific events and characteristics explain why some countries score higher when using a quantitative measure instead of a questionnaire survey. For the United States, Russia and China, we believe that this could be the case. In the case of Kenya, it is difficult to identify a reason for the extremely high value observed in the index compared to the survey measure. Instead, the underlying methodological differences could possibly explain why the two measures are somewhat incompatible.

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A. Appendix

A.1 Questionnaire

The multiple choice question in the Global Consumer Survey from Statista (2020b) regarding CAR was stated in the following way:

”Which of these financial products and investments do you currently use/own?”

A.2 Included Countries

CAR: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czechia, Denmark, Dominican Republic, Egypt, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Serbia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom, United States and Vietnam.

CAI: Same as CAR, except for Taiwan. The ”Africa and Central Asia” regressions also include Algeria, Bangladesh, Ethiopia, Ghana, Iran, Kazakhstan, Myanmar, Sudan, Uganda, Ukraine, Uzbekistan and Venezuela.

BTV: Same as CAR, except for Austria, Belgium, Egypt, Finland, France, Germany, Greece, Ireland, Israel, Italy, Poland, Portugal, Romania, Serbia, South Korea, Spain and Taiwan.

A.3 Additional Regressions

In Tables A.1 and A.2, regression outputs are provided when no control variables are included in the model. Compared to the first-stage in Table 5.1, smartphone penetration has a smaller but still positive impact on financial access, which is significant at the 0.1% significance level. Without any controls, financial access has a greater impact, compared to 5.3, and it is significant at the 1% significance level.

Table A.1: Account Ownership: First-stage Regression Output, Controls Omitted

	(1)
	Account Ownership
Smartphone Penetration	0.010*** (0.001)
Constant	0.213** (0.073)
Observations	55

Robust standard errors in brackets.

First-stage regression estimates using account ownership as the endogenous variable. No controls are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: CAR: OLS and IV Regression Output, Controls Omitted

	(1)	(2)
	CAR	CAR
Account Ownership	-0.123** (0.039)	-0.153** (0.051)
Constant	0.192*** (0.034)	0.216*** (0.044)
Observations	55	55

Robust standard errors in brackets.

OLS and IV regression estimates, using CAR as the dependent variable, are provided in column 1 and 2, respectively. Again, no controls are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tables A.3 and A.4 provides the output using standardised variables. When standardised, the units of measurement are eliminated, and the variables are instead measured in units of standard deviation, which is used to explore the importance of the included variables when they are measured in different units. It is done by checking the magnitude of the coefficient estimates. A higher coefficient estimate implies that a change in the independent variable related to the estimate has a bigger impact on the dependent variable. An increase of one standard deviation in smartphone penetration generally results in a 0.722 standard deviation increase in financial access, holding the other included variables fixed, given in Table A.3. This result is significant at a 0.1% significance level. Also, from Table A.4 it can be seen that a standard deviation increase in financial access results on average in a decrease of 0.358 standard deviations in CAR when running an OLS regression, holding all other variables included fixed. The IV regression estimate of 0.400 can be interpreted similarly. Both coefficient estimates are significant on the 5% significance level.

Table A.3: Account Ownership: Standardised First-stage Regression Output

	(1)
	Account Ownership
Smartphone Penetration	0.722*** (0.112)
Bank Branches	-0.002 (0.075)
Muslims	-0.280** (0.095)
Latitude	-0.015 (0.121)
Constant	0.044 (0.147)
Regional Controls	YES
Observations	55
Kleibergen-Paap's F-statistic	41.399

Robust standard errors in brackets.

First-stage regression output showing the relationship between smartphone penetration and financial access, measured using account ownership. The continuous variables are standardised.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: CAR: Standardised OLS and IV Regression Output

	(1)	(2)
	CAR	CAR
Account Ownership	-0.358* (0.171)	-0.400* (0.187)
Bank Branches	-0.021 (0.107)	-0.022 (0.096)
Muslims	-0.147 (0.171)	-0.162 (0.155)
Latitude	-0.553** (0.189)	-0.541** (0.165)
Constant	0.218 (0.213)	0.225 (0.198)
Regional Controls	YES	YES
Observations	55	55

Robust standard errors in brackets.

Regression output using CAR as the dependent variable.

In column 1, the OLS regression estimates are provided.

In column 2, the IV regression estimates are provided.

The continuous variables are standardised.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table A.5, the results are shown from the OLS regression using account ownership as a measure of financial access and CAI as the dependent variable in column 1. The coefficient estimate of interest is not significant on the 5% significance level. In column 2, BTV is the dependent variable in the OLS regression and suggests that financial access positively impacts BTV, and the coefficient of interest is significant on the 5% significance level.

Table A.5: CAI and BTV: OLS Regression Output

	(1)	(2)
	CAI	BTV
Account Ownership	-0.099 (0.150)	1.667* (0.773)
Bank Branches	0.001 (0.001)	0.015 (0.008)
Muslims	-0.237* (0.089)	-0.057 (0.359)
Latitude	0.008 (0.183)	-0.400 (0.713)
Constant	0.217 (0.148)	-0.430 (1.079)
Regional Controls	YES	YES
Observations	54	36

Robust standard errors in brackets.

OLS regression estimates using CAI as the dependent variable in column 1, and BTV in column 2.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The continuous variables in Table A.6 are standardised. A change of one standard deviation in financial access on average results in a 0.505 standard deviation decrease in CAI and a 0.377 standard deviation increase in BTV, holding all other variables in the model fixed. Both results are significant at the 5% significance level.

In Table A.7, other results from the IV regressions, using digital transaction as a measure of financial access are presented. In column 1, the dependent variable is CAI, and in column 2, the dependent variable is BTV. Both results are significant at the 5% significance level. Again, the results follow the results from previous regression with a negative effect when focusing on CAI and a positive effect when focusing on BTV, with similar magnitudes.

Table A.6: CAI and BTV: Standardised IV Regression Output

	(1)	(2)
	CAI	BTV
Account Ownership	-0.505*	0.377*
	(0.229)	(0.162)
Bank Branches	0.109	0.219*
	(0.117)	(0.094)
Muslims	-0.513**	-0.008
	(0.161)	(0.090)
Latitude	0.122	-0.109
	(0.254)	(0.161)
Constant	-0.320	-0.037
	(0.226)	(0.348)
Regional Controls	YES	YES
Observations	54	36

Robust standard errors in brackets.

IV regression estimates using standardised continuous variables. In column 1, CAI is used as the dependent variable. In column 2, BTV is used as the dependent variable.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: CAI and BTV: Additional IV Regression Output

	(1)	(2)
	CAI	BTV
Digital Transactions	-0.316*	1.478*
	(0.135)	(0.630)
Bank Branches	0.002	0.010
	(0.001)	(0.006)
Muslims	-0.289**	-0.171
	(0.091)	(0.267)
Latitude	0.111	-0.453
	(0.177)	(0.633)
Constant	0.288*	0.048
	(0.134)	(0.772)
Regional Controls	YES	YES
Observations	54	36

Robust standard errors in brackets.

IV regression outputs for the dependent variables CAI and BTV. Column 1 provides IV estimates using CAI as the dependent variable. Column 2 provides the IV estimates using BTV as the dependent variable. Both columns use digital transactions as a measure of financial access.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Africa and Central Asia

In Table A.8, the first-stage regression results are provided when including more countries located in Africa and Central Asia. It indicates that the instrument is still relevant with a significant coefficient estimate on smartphone penetration, and a high F-statistic.

Table A.8: Account Ownership: First-stage Regression Output

	(1)
	Account Ownership
Smartphone Penetration	0.812*** (0.092)
Bank Branches	0.002* (0.001)
Muslims	-0.145 (0.068)
Latitude	0.000 (0.000)
Constant	0.305*** (0.083)
Regional Controls	NO
Observations	62
Kleibergen-Paap's F-statistic	77.278

Robust standard errors in brackets.

First-stage regression output showing the relationship between smartphone penetration and financial access, measured using account ownership, with coefficient estimates reported in column 1.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table A.9 we present the IV estimates when including more African and Central Asian countries. We note that the coefficient estimate of interest is still negative and significant.

Table A.9: CAI: IV Regression Output

	(1) CAI
Account Ownership	-0.561** (0.194)
Bank Branches	-0.000 (0.002)
Muslims	-0.352*** (0.102)
Latitude	0.000 (0.001)
Constant	0.662*** (0.157)
Regional Controls	NO
Observations	62

Robust standard errors in brackets.

IV regression output showing the relationship between smartphone penetration and financial access, measured using account ownership, with coefficient estimates reported in column 1.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Income and State Illegitimacy

In Table A.10, the result from the first-stage regression, including GDP per capita in 2017, using account ownership as a measure of financial access and CAR as the dependent variable, is presented. We note that the estimated coefficient for smartphone penetration is significant at the 5% significance level but higher than the case without GDP per capita in 2017. It should be clear that we do not consider GDP per capita to be an appropriate control, but we include it for transparency. Furthermore, we include this to show the reader concerned about the potential effect of such variables on our results. It does not result in insignificant estimates but instead indicates that GDP per capita does not impact financial access. The coefficient estimate on smartphone penetration is now higher without this variable. A similar analysis can be made for Table A.11 when considering the effect of financial access on CAR.

First-stage regression output when including state illegitimacy is provided in Table A.12. As proposed by previous literature, it is a factor that may impact the adoption of cryptocurrencies. As some may believe that it is an omitted variable, we include it in our regression to show that the results do not change. In Table A.13 we note that the coefficient estimate on account ownership is still negative and similar in magnitude and significance. As with GDP per capita, state illegitimacy is considered a bad control and is only included for transparency. The effect of account ownership on CAR could be mediated by including state illegitimacy in our regressions and the reason for the insignificant relationship in the OLS framework.

Table A.10: Account Ownership: First-stage Regression Including GDP per Capita

	(1)
	Account Ownership
Smartphone Penetration	0.821*** (0.160)
GDP/capita in 2017	0.000 (0.000)
Constant	0.251** (0.076)
Observations	54
Kleibergen-Paap's F-statistic	26.364

Robust standard errors in brackets.

First-stage regression output using account ownership as measure of financial access, and including GDP per capita in 2017 on the right-hand side of the equation. Controls are omitted from the model.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11: CAR: OLS and IV Regressions Including GDP per Capita

	(1)	(2)
	CAR	CAR
Account Ownership	-0.109* (0.048)	-0.221* (0.113)
GDP/capita in 2017	-0.000 (0.000)	0.000 (0.000)
Constant	0.188*** (0.036)	0.243*** (0.068)
Observations	54	54

Robust standard errors in brackets.

OLS and IV regression estimates (in column 1 and 2, respectively) using CAR as the dependent variable, and account ownership as the independent variable, and including GDP per capita in 2017 on the right-hand side of the equation. Controls are omitted from the model.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.12: Account Ownership: First-stage Regression with State Illegitimacy

	(1)
	Account Ownership
Smartphone Penetration	0.747*** (0.123)
State Illegitimacy	-0.005*** (0.001)
Constant	0.505*** (0.097)
Observations	55

Robust standard errors in brackets.

First-stage regression output using account ownership as measure of financial access, and including state illegitimacy on the right-hand side of the equation.

Controls are omitted from the model.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.13: CAR: OLS and IV Regressions with State Illegitimacy

	(1)	(2)
	CAR	CAR
Account Ownership	-0.082 (0.044)	-0.148* (0.070)
State Illegitimacy	0.001 (0.000)	0.000 (0.001)
Constant	0.138** (0.044)	0.209** (0.070)
Observations	55	55

Robust standard errors in brackets.

OLS and IV regression estimates (in column 1 and 2, respectively) using CAR as the dependent variable, and account ownership as the independent variable, and including state illegitimacy on the right-hand side of the equation. Controls are omitted from the model.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$