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Cryptocurrency Regulation: Insights from Demographics, Crime Rates, and Traditional Banking

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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This paper explores the predictors of cryptocurrency ownership using the U.S. Survey of Consumer Payment Choice and crime data from the Federal Bureau of Investigation. We find that adoption of financial technology, being Asian or other race, and moving from high school to Bachelor's degree are positive predictors of cryptocurrency ownership. Female, Hawaiian, and older Americans are less likely to own cryptocurrency. When predicting ownership of specific cryptocurrencies, we see that these predictors fluctuate, suggesting that certain groups of investors prefer different coins. The popularly held belief that theft and cryptocurrencies are positively interlinked is confirmed, but violent crime is negatively associated. Lastly, we find that paying a credit card or bank account fee in the last year that indicates financial illiteracy has a positive effect on cryptocurrency ownership.

Predicting Cryptocurrency Ownership in America

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Dr. Banerjee's class in Industrial Organization exposed me to how economics can be used to understand what regulation is best.

Contents

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Niels Armbruster

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1 Introduction

1.1 Overview

Cryptocurrency ownership has doubled since 2021, and has a current market capitalization equivalent to prominent companies, such as Berkshire Hathaway, Walmart, and Amazon (Cap, 2025; Blackstone, 2025). Currently, cryptocurrency regulation is mostly a patchwork, with different regulations at the state and federal level that make it challenging for investors and issuers. This creates a stain on the legitimacy of crypto and hinders its ability to grow (Chen, 2025). The goal of this paper is to understand the motivations behind cryptocurrency ownership, and how those can inform regulation.

To do this, we use the Survey of Consumer Payment Choice courtesy of the Federal Reserve Bank of Atlanta to test several hypotheses regarding cryptocurrency ownership. This data is a household survey from 2022 that measures demographics, payment preferences, and currency/asset holdings. From this data, we aim to construct multiple regression models to determine the relationship between these variables and cryptocurrency ownership. Additionally, we use crime data from the Federal Bureau of Investigation and population data from the United States Census Bureau to analyze how crime rates impact cryptocurrency ownership.

First, we analyze how adoption of financial technology, demographics, education levels, and sentiments on traditional banking impact cryptocurrency ownership. We find that those who are more"digitized", individuals belonging to "other race" or Asian racial categories, and Bachelor's Degree graduates (compared to high school graduates), are more likely to own cryptocurrency. Female, older, and Hawaiian/Pacific Islander respondents are less likely to own cryptocurrency. Importantly, we also see that sentiments on traditional banking have no significant impact on crypto ownership, suggesting that cryptocurrency is treated as an investment, not an asset, which helps to solve perhaps the most polarizing question regarding crypto.

Next, we see how these predictors fluctuate for specific cryptocurrencies. We see that there are substantial differences across these groups, suggesting that regulation of cryptocurrencies should not be a one size fits all approach. Specifically, women are negatively associated with ownership of all cryptocurrencies, but positively associated for Bitcoin.

Then, we analyze how crime rates impact cryptocurrency ownership, and we see that respondents that the theft rate in the respondent's area is positively associated with crypto ownership, but violent crime is negatively associated. From this we can ascertain that theft may drive people to invest in crypto as it is more difficult to steal, or that crypto is purchased as it is easier to use to sell stolen goods.

Lastly, when using a two stage approach with a copula, we find that paying a "risky" credit card or bank account fee (bounced check, cash advance, late payment, low balance, over limit, or overdraft fee) in the last year has a positive Average Treatment Effect (ATE) on ownership. This highlights that cryptocurrency is popular among the financial illiterate, suggesting that cryptocurrencies should have strong regulation against scams.

1.2 Economic Theory

Before completing our analysis, we look towards existing fields of economics to explain how the variables we use will affect cryptocurrency ownership. To highlight the importance of this research, we note that institutional economics suggests that the current, confusing regulatory structure hinders cryptocurrency growth. Furthermore, the field also offers that low trust in traditional banking systems would result in higher crypto ownership. Next, we expect certain demographics to be more adopting of cryptocurrency, which could be partially caused by different levels of risk aversion. Specifically, behavioral economics tell us that risk averse people (women and people in high crime areas, for example) are less likely to own cryptocurrency as it is a risky asset (Brown et al., 2017).

We also analyze what the nexus of law and economics has to say about cryptocurrency ownership. Crime is often linked to cryptocurrency, so we conclude that theft in the area will make cryptocurrency a comparatively safer asset, increasing its popularity. Information economics is also a key way to explain differences in crypto adoption. Cryptocurrency is a new and complicated asset class, so there is significant information asymmetry. Particularly, we expect those with higher education and who adopt financial technology to have a higher understanding of digital assets, leading to higher cryptocurrency ownership.

Labor economics suggests there would be an income effect for cryptocurrency ownership. When respondents have more disposable income, they are more able to invest in risky assets, such as cryptocurrency.

1.3 Literature Review

1.3.1 Cryptocurrency Origins

Cryptocurrency began in 2008 with the founding of Bitcoin by someone using the pseudonym Satoshi Nakamoto. In the white paper that details the reasoning for creating a cryptocurrency, Nakamoto writes "What is needed is an electronic payment system based on cryptographic pro of instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party" (Nakamoto, 2008).

1.3.2 Current Cryptocurrency Regulation

Because of the relative novelty of cryptocurrency compared to other financial tools, regulators are still deciding how to address all the concerns that crypto raises. Currently, cryptocurrency is regulated at both a state and federal level. At the state level, regulations differ across each state, making it hard for creators of cryptocurrencies to use their coins nationally as registration is required in different states (Jasperse, 2023). At the federal level, there are challenges in determining if cryptocurrency is an asset, and if so, what regulatory body should regulate it. The two primary federal regulatory bodies that would take cryptocurrency under their purview are the Commodity Futures Trading Commission (CFTC) and Securities and Exchange Commission (SEC). The principle difference between these two is that the CFTC regulates the purchases of commodities for future delivery, and the SEC regulates assets if they meet the four-step Howey Test. The Howey test determines that an asset is a security if it is an investment of money, there is an expectation of profits from the investment, the investment of money is in a common enterprise, and any profit comes from the efforts of a promoter or third party. Ultimately, the difference in classification leads to the CFTC and SEC attempting to exert regulatory control over some of the same cryptocurrencies (Emmert, 2023).

A particular legal case that highlights the confusing nature of cryptocurrency regulation is *SEC v Ripple Labs*. Ripple Labs created a cryptocurrency called XRP beginning in 2011, but the SEC only filed suit in 2020 following a $1.3 billion sale because XRP was not registered with the SEC. Specifically, the suit argued that Ripple Labs had been in violation of SEC rules from 2013 to 2020, but there was no enforcement action taken. In the case, Ripple Labs noted that it was unfair to allow XRP to grow without a hint of enforcement, only to bring a suit later. Examples such as these disincentivize the creation of new cryptocurrencies, which can cause significant economic growth. If new cryptocurrency founders want to see if they need to be registered with the SEC upon entering the market, they can provide the details behind their coin and ask for a "No Action Letter". However, the SEC is not required to review every no-action request, writing the request is quite time consuming, and if any details change, the no-action letter is void (Emmert, 2023).

Another cause for concern with cryptocurrency regulation is that it is not very front footed. Because of the confusion on whether or not a coin is regulated by either the CFTC or SEC, many initial coin offerings (ICOs) take place without any regulation or registration in place. This is particularly important considering that the vast majority of ICOs are scams (Daniel Araya, 2018). Therefore, consumers that are harmed are required to get retroactive damages, rather than the regulatory body restricting the offering. If the regulation of cryptocurrencies was clearer, regulators could require registration before issuance, meaning that harm and social cost would be minimized.

The lack of clear and precise regulation for cryptocurrency in the United States creates a real threat that cryptocurrency operations would be stifled (Grennan, 2022).

1.3.3 Cryptocurrency Regulation Prescriptions

To solve the issues involving cryptocurrency regulation, it is important to first understand the predictors of cryptocurrency ownership. After finding those results, we can determine what economic issues need to be solved by regulation.

There are instances of economic research on the motivations behind cryptocurrency research, with other researchers finding that traditional banking sentiments may not have a significant impact on ownership (Auer and Tercero-Lucas, 2021). Furthermore, researchers have estimated the importance of cryptocurrency regulation by using game theory to demonstrate that a lack of clear regulation hinder cryptocurrency growth (Cong et al., 2024). Crime related research to cryptocurrency is primarily limited to analyzing trends in crimes and attempting to detect crime related cryptocurrency transactions, but not the level of crime in the respondent's area (Foley et al., 2019).

This paper adds onto existing research by connecting survey and empirical data to see how a multitude of factors affect cryptocurrency ownership. To my knowledge, the use of a bivariate copula to measure dependence between fee payments and cryptocurrency ownership is the first of this kind. In essence, this paper determines how cryptocurrency ownership is affected by demographics, fee payments, crime rates, sentiments on traditional banking, and the adoption of financial technology. The combination of these variables is unique to the existing research.

2 Data

2.1 Survey of Consumer Payment Choice

This paper uses data from the University of Southern California and the Federal Reserve Bank of Atlanta, which is called the Understanding America Study. The Understanding America Study is administered yearly by the University of Southern California and contains roughly 15,000 respondents. From that dataset, the Federal Reserve Bank of Atlanta provides a subset of data that provides data about consumer preferences on currency and payment behavior called the Survey of Consumer Payment Choice (SCPC) (FRBA, 2022).

The SCPC contains information on a transactional and individual level. Given that this paper aims to gain inference about individual choices regarding payment behavior and currency holdings, we opt to use the individual waves of information. When we began research on this topic, the most recent data was from 2022, but since then the Federal Reserve Bank of Atlanta has posted their results for 2023. We use the data from 2022, which has 4,719 respondents.

The most important outcome variables that are we are interested in are the binary variables of cryptocurrency ownership and knowledge. Respondents answer whether or not they own or have knowledge of cryptocurrency. If they respond yes, a value of 1 is entered, and if no, a value of 0. Additionally, they are asked if they own specific types of cryptocurrency, namely Bitcoin, Ethereum, Litecoin, Dogecoin, or any other cryptocurrency. Next, respondents are asked similar questions about whether or not they use a credit card, mobile payment app, or PayPal. Then, respondents answer basic demographic questions such as their marital status, age, retirement status, gender, race, county type, and state of residence. Furthermore, they select which level of education is the highest they attained. Also, respondents rank the security and convenience of cash, bank accounts, and online banking on a scale from 1 to 5.

The survey also provides data if the respondent has paid certain types of fees in the last year. For our analysis, we are interested in whether the respondent has paid a bounced check, cash advance, late payment, low balance, over limit, or overdraft fee. Table 4 is a Data Dictionary which describes the variables included in our regression analysis. Weights are also included for each respondent, which we use to make the most accurate calculations in our descriptive statistics and regression results.

2.2 National Incident-Based Reporting System

The Federal Bureau of Investigation supplies the National Incident-Based Reporting System (NIBRS). We use the 2022 data which details each crime incident in the United States, what crimes were committed, and what county the crime occurred in (USBJ, 2023)

2.3 US Census Bureau Data

We utilize two datasets from the the US Census Bureau. First, we use data from the 2020 census that is aggregated by county and provides information about how many rural or urban census blocks are within each county (USCB, 2023a) Second, we use another data source to find the estimated population for 2022 by county (USCB, 2023b).

3 Descriptive Statistics

3.1 Variable Distributions

Before calculating descriptive statistics, we employ minimal data cleaning to ensure our data is visually presentable. First, we opt to calculate the highest level of education each respond achieved. Rather than having numbers ranging from 0 to 16, we convert these to elementary, middle school, high school, bachelors, and graduate. For the respondent to fit in each of those bins, they must have graduated from that level of education. For the income and age variables, we bin the data by relevant amounts, and then make a weighted count per bin. Lastly, for the marital status variable, values om the dataset range from 1-6, which we alter to a binary variable based on whether or not the respondent is legally married, regardless of where their spouse lives. All of these calculations use the sample weights to provide the most accurate proportions.

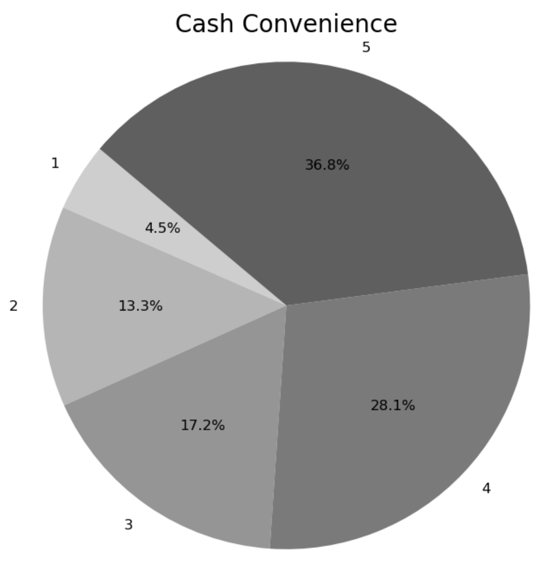

Figure 1: Cash Convenience

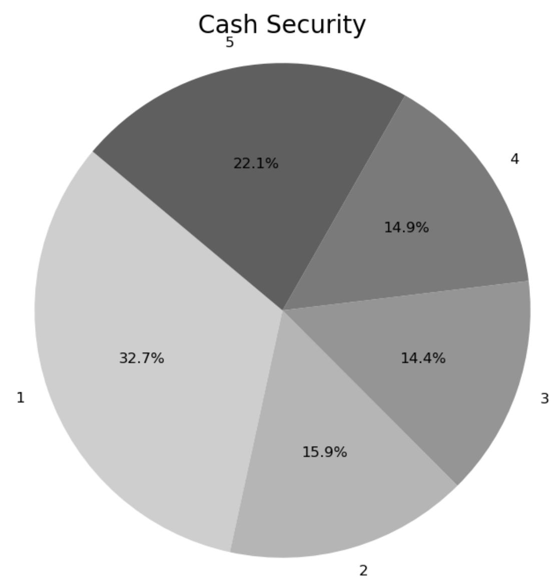

Figure 2: Cash Security

Above, a pie chart of respondents opinions on the convenience and security of cash are included. As demonstrated visually, respondents find cash highly convenient, with the two highest proportions belonging to convenience levels 4 and 5. For cash security, we see the opposite, where respondents find that cash is not secure, with the two highest proportions at security levels 1 and 2.

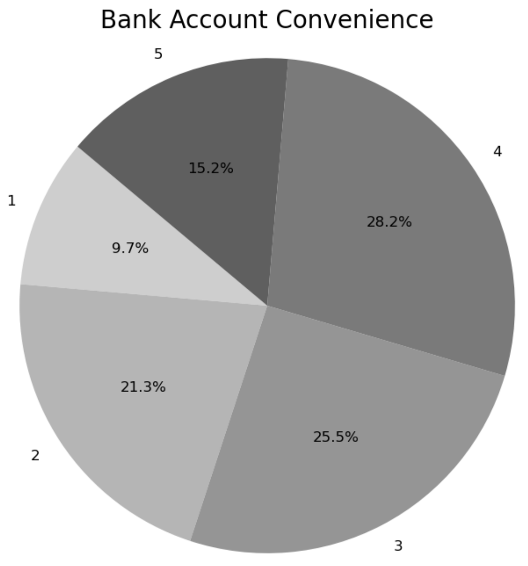

Figure 3: Bank Account Convenience

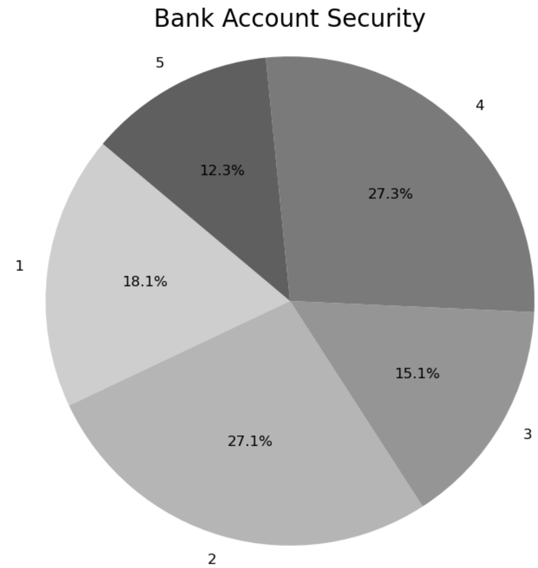

Figure 4: Bank Account Security

Above, we depict the same pie charts as earlier, but this time for bank account convenience and security. We find that most respondents rank bank accounts as slightly above average when it comes to convenience, as the highest proportion falls in convenience levels 3 and 4. For bank account security, we see that most respondents either find them to have slightly above average or slightly below average security, with 2 and 4 being the most frequent responses.

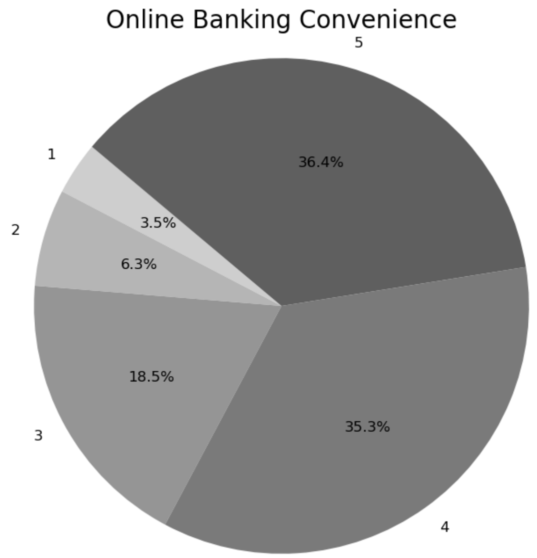

Figure 5: Online Banking Convenience

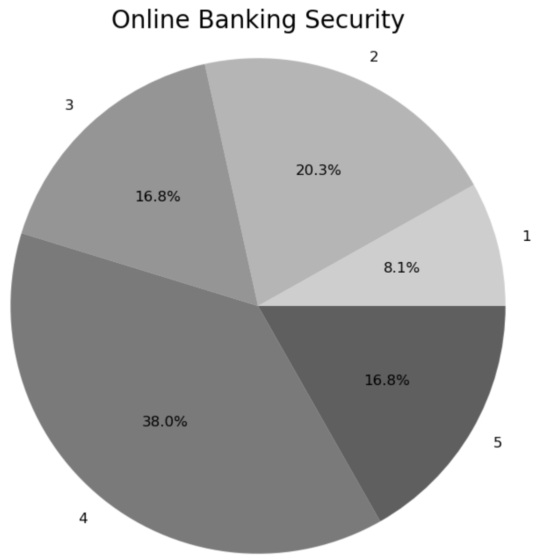

Figure 6: Online Banking Security

The last convenience and security method of payment that we have data for is online banking. Here, we see that respondents find online banking to be quite convenient, with most of the respondents ranking it with a convenience level of 4 or 5. For security, we see that most respondents find it have slightly above average, with ranking at a security level of 4.

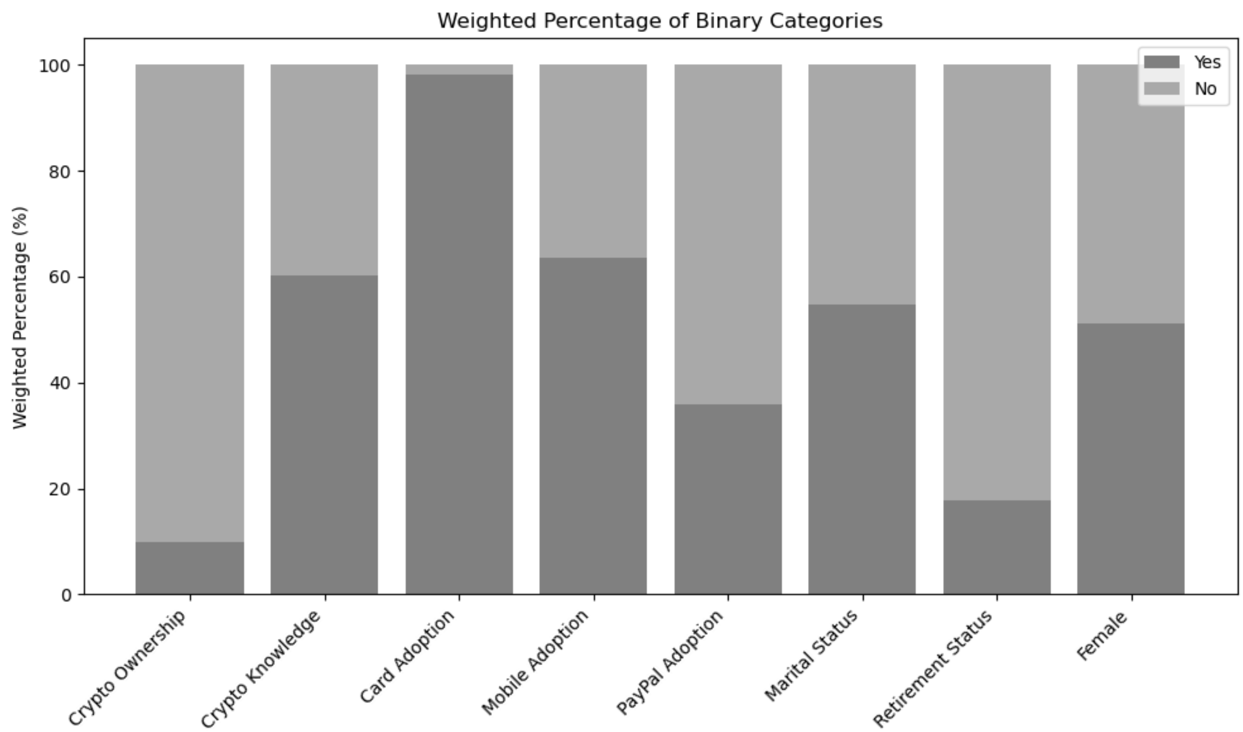

Figure 7: Binary Variables

In our data, we have numerous binary variables, meaning they take on values of either 0 or 1. The outcome variable of most of our analysis is cryptocurrency ownership, which measures whether or not a respondent owns cryptocurrency. We see that this is less than 10% of the population, so it is quite an anomaly that a respondent owns cryptocurrency. Next, we see that knowledge of cryptocurrency is much more prevalent, with roughly 60% of respondents saying that they are aware of at least one type of cryptocurrency.

The next three variables measure respondents' adoptions of different types of financial technology. First, almost all respondents have a payment card. Second, over 60% of respondents use some mobile app to make payments. Lastly, we see that just under 40% of respondents use PayPal.

The last three binary variables that we include in our regression measure basic demographic information of the respondents. First, roughly 50% of respondents are married. Second, less than 20% of respondents are retired. Lastly, just over 50% of the sample are women. As these results are weighted, it is no surprise that these align with the same statistics of the US population.

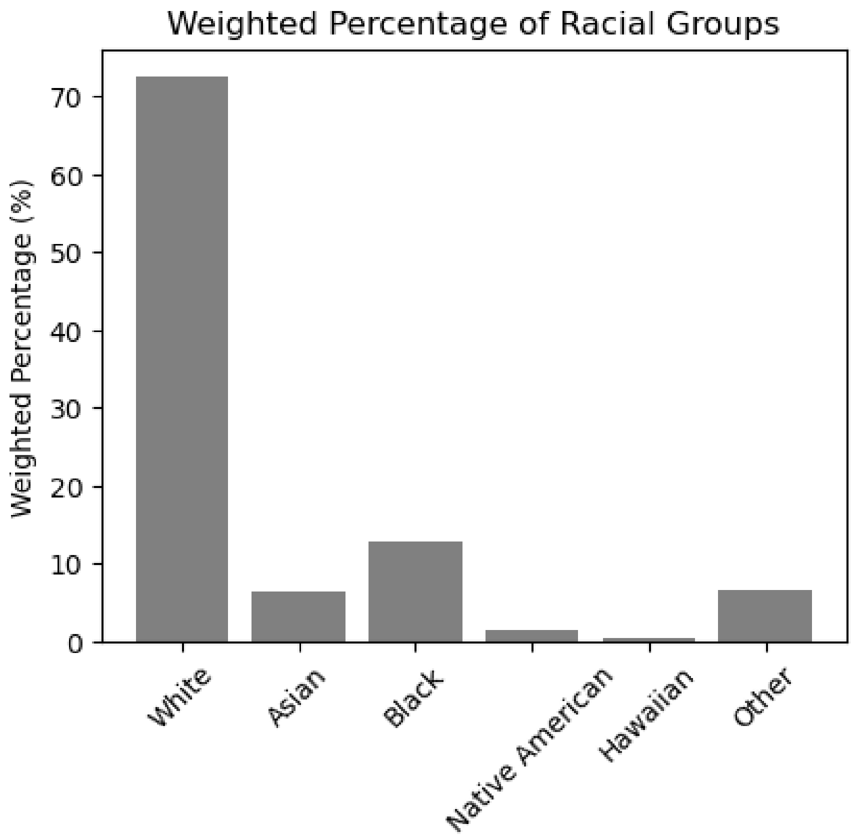

Figure 8: Racial Variables

Next, we include racial data in our regression. One of the primary reasons to include this data is that forefront literature on cryptocurrency ownership and investment suggests there are different cryptocurrency ownership behavior among different racial groups. Here, we see that the sample is quite representative of the US population after weighting. All of these weighted percentages match up closely with what is recorded by the US Census Bureau.

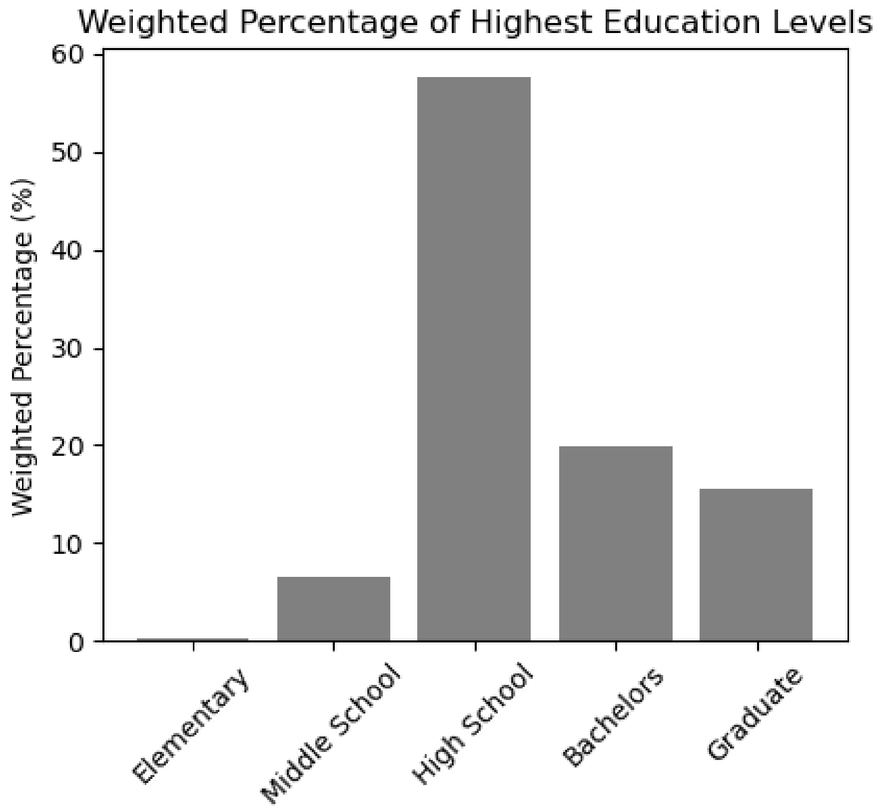

Figure 9: Highest Level of Education

Now, we include descriptive statistics about the highest level of education that respondents in the sample have achieved. As mentioned in the beginning of this section, the raw data is presented with levels ranging from 1-16, each measuring a specific year as the highest level of education. We believe that grouping these levels by typical academic divisions allows us to make reliable conclusions about the data. Here, we see that most of the respondents only graduated high school, followed by those with a bachelors degree and graduate degree. A very small portion of the sample was only educated through middle school, and a minuscule amount only completed elementary school.

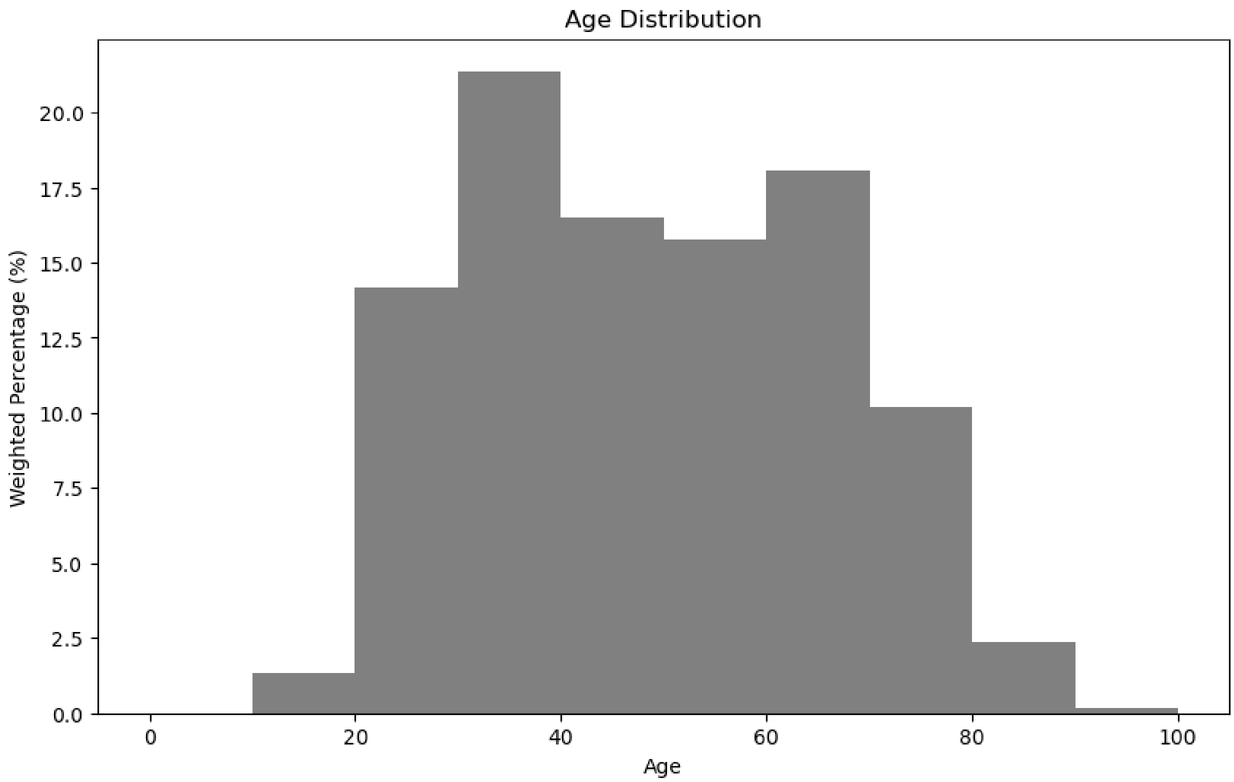

Figure 10: Age

Above, we present the age data for the sample. As mentioned in the introduction to this section, we binned by a certain number, then counted the number of respondents within that bin, and finally multiplied that result by the sampling weight to find the weighted percentage per bin. One important factor to note is that only legal adults are sampled, meaning that the sample is restricted to only those above the age of 18. As we see visually, most of the sample is between 20 and 40, followed between those from 40 to 60. The number of respondents between 60 and 70 is fairly high, which could be cause by the Baby Boom. Following that, the amount of respondents dwindles, with only a few respondents above the age of 90. We find that this is quite similar to what the US Census Bureau data suggests, which makes sense as the data is weighted.

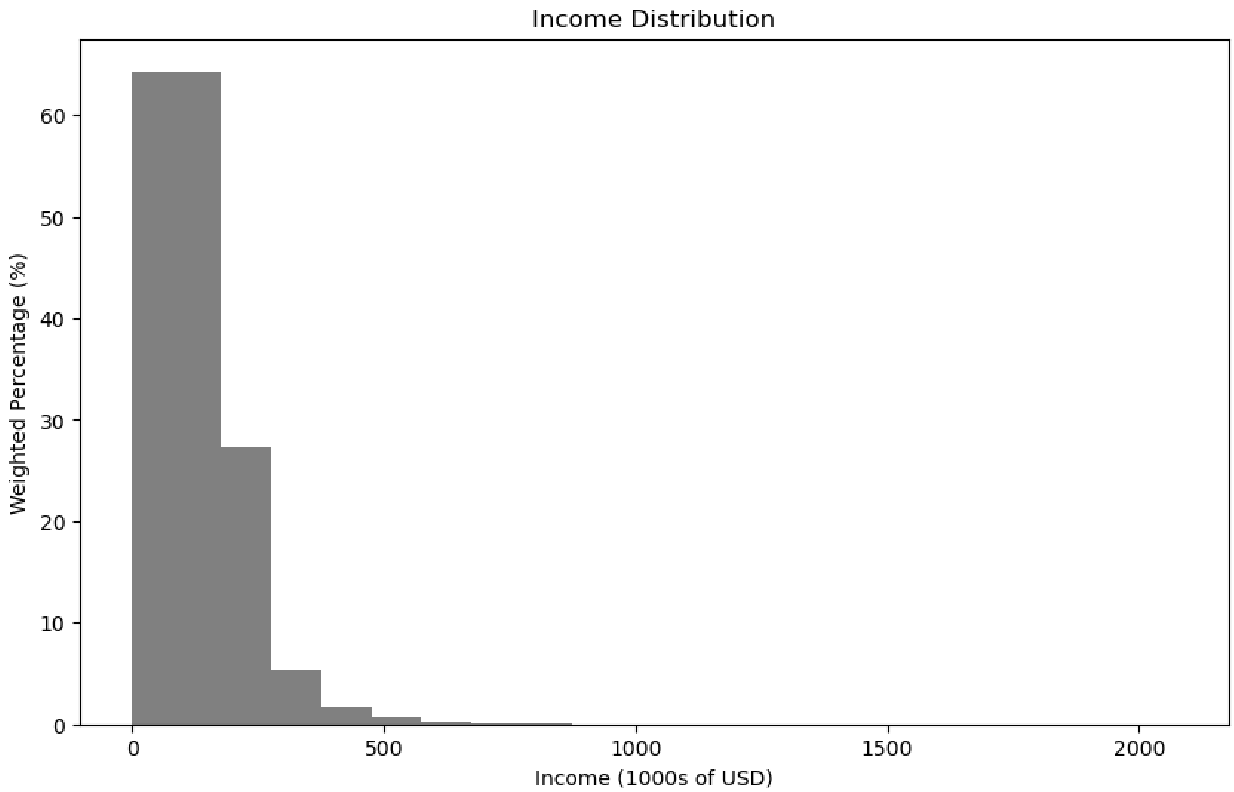

Figure 11: Income

The next descriptive statistic that we provide is the household income of respondents. Here, we can see that there is a strong right skew, and most respondents make less than \$100,000 USD. The data certainly has an outlier as one respondent reports an incoem of \$1.75 million in 2022. All in all, we see that there is a mean income of \$87,000. We believe that this will be an important aspect to include in our regression as traditional economics suggests there would be a income effect on ownership.

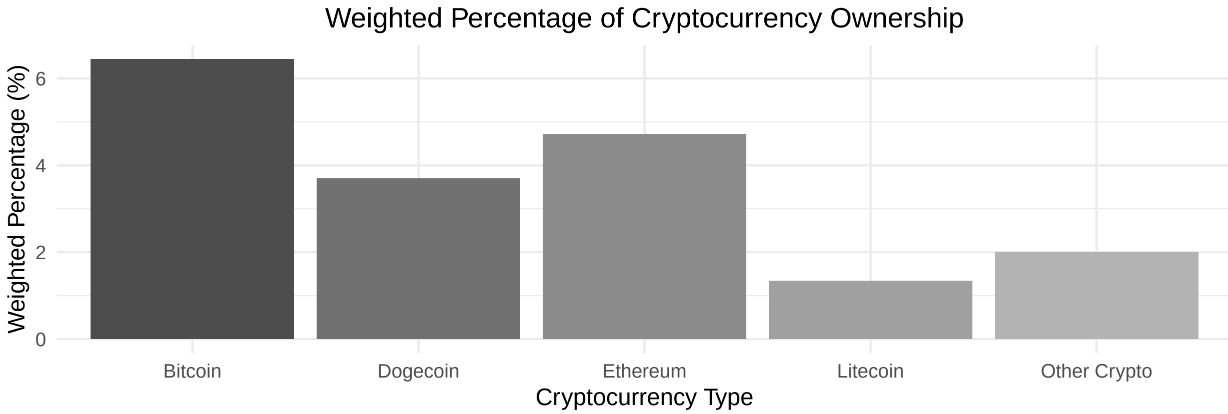

Figure 12: Weighted Percentage of Cryptocurrency Ownership

We also provide the information about the distribution of cryptocurrency ownership across different types of cryptocurrency. Bitcoin is the most popular cryptocurrency, with Ethereum second, and Dogecoin is third. Then, there is a significant drop off when it comes to Litecoin, which is less than 2% of the sample. We also have data on what percentage of respondents own cryptocurrencies other than these four. This graph suggests that ownership of cryptocurrency is quite top heavy, as other crypto is only more popular than Litecoin ownership, despite there being thousands of other cryptocurrencies.

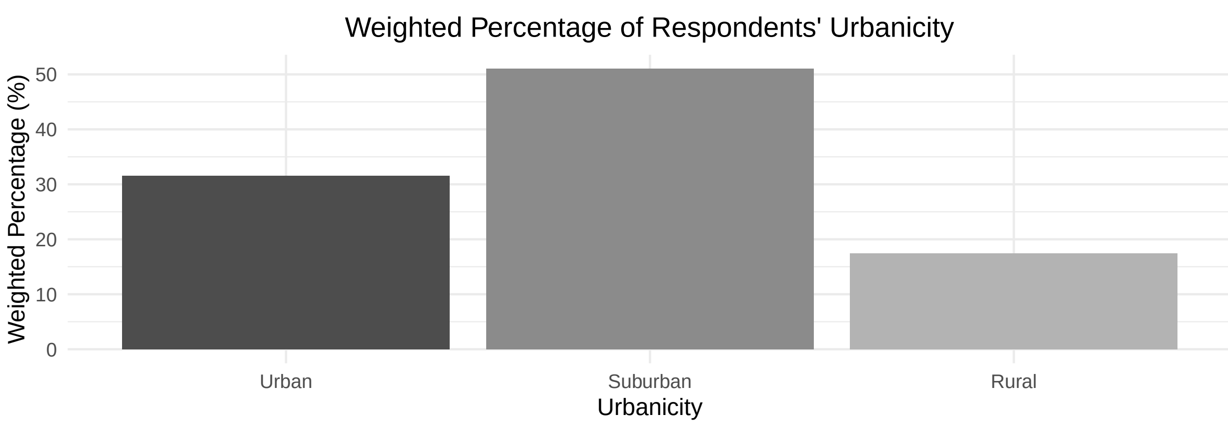

Figure 13: Weighted Percentage of County Classification

Here, we report the weighted percentage of the county classification of each respondent.

As this is a representative sample of the United States, we see similar metrics to what we would expect. Most respondents live in suburban areas, followed by urban areas, and lastly rural areas.

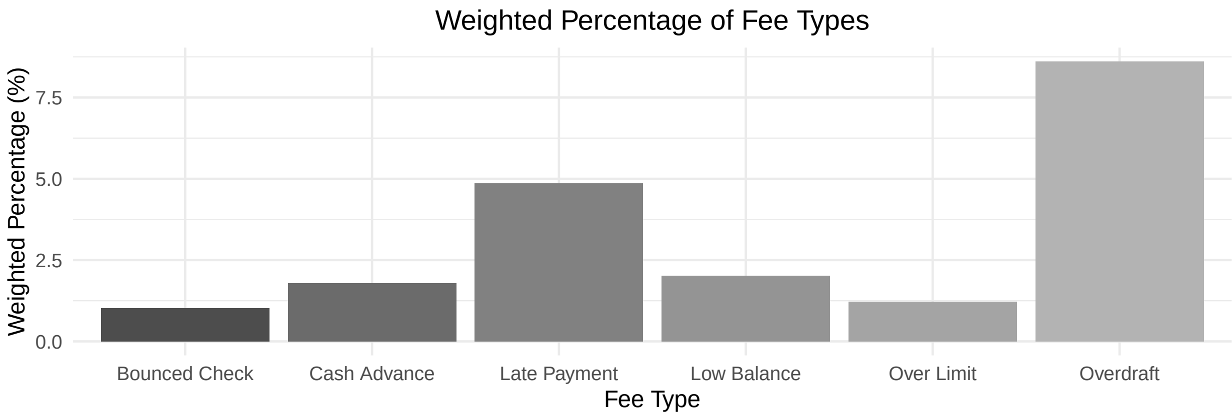

Figure 14: Fee Types

Lastly, we include information about what percent of respondents have paid fees in the last year. We see that the most common fee is an overdraft fee, with late payment fee being the second most common.

3.2 US State Heat Map

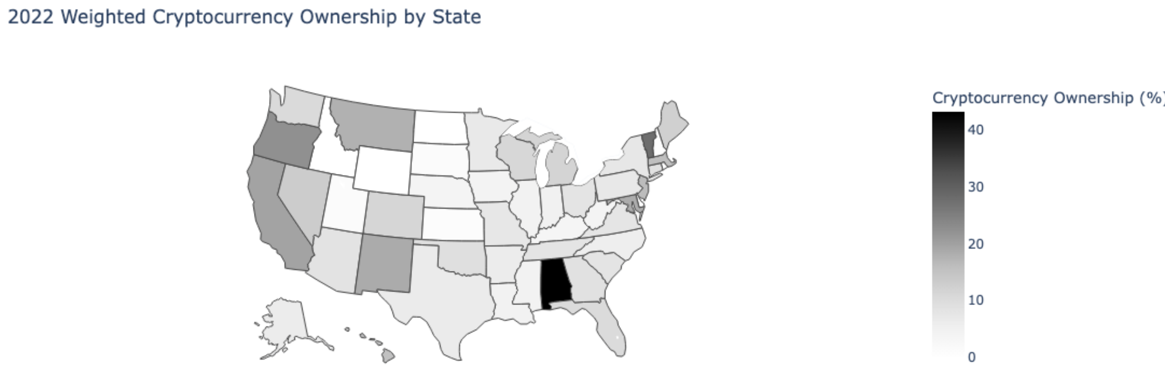

Figure 15: US State Heat Map

Here, a figure is provided that depicts the weighted proportion of cryptocurrency ownership by state in the United States. The state of Alabama stands out as having the highest cryptocurrency ownership of all 50 American states.

The primary reason Alabama has such a high rate of cryptocurrency ownership is because of the way that many popular cryptocurrencies, such as Bitcoin, verify transactions. Some cryptocurrencies are originally created and obtained through a process known as mining, where computers run through numerous, computationally heavy calculations. The purpose of mining is to ensure that new transactions are accurate and verified, which are then chained on with a new block, giving the name blockchain. In the case of Bitcoin, miners are attempting to guess a 64 digit hexadecimal number before anyone else so they receive Bitcoin in return, but spend large amounts on energy and computing power. This is known as a "proof of work" system, as miners must show that they have correctly guessed the number. For some other popular form of cryptocurrencies such as Ethereum, miners instead put up a stake of Ethereum and the miner with the highest stake is given exclusive right to guess the number. Because of the different mechanism, this is known as a "proof of stake" system (Coinbase, 2024).

Bitcoin currently gives a reward of 3.125 Bitcoin to someone who correctly guesses the number, which is worth $332,687.19 as of January 2025 (Coinbase, 2024; TabTrader, 2025). The reward for Bitcoin mining has been regularly halved since its inception, as the reward began at 50 Bitcoins. This process is necessary because there are only 21 million Bitcoin available, so scarcity is preserved.

The state of Alabama has what is known as a "low utility rate," meaning that electricity, water, and gas are cheaper to acquire than in other parts of the country. As cryptocurrency mining requires lots of energy and water to fuel and cool the computers that do the mining, Bitcoin mining companies have flocked to Alabama to set up operations for higher profit margins (Martin et al., 2024). Higher amounts of Bitcoin mining would have a two-fold effect on cryptocurrency ownership in Alabama. First, if companies move their operations to Alabama, there will certainly be more people there who own cryptocurrency. Furthermore, the mining operations will expose people living in the state to the viability of cryptocurrency, which may lead to them investing or purchasing one of the more popular cryptocurrencies.

One important conclusion that is challenging to glean from this graph because of its minute geographical size is that Washington DC has a higher proportion of cryptocurrency ownership compared to the 50 states. The primary reason why Washington DC has such a high rate is likely because of its unique status as the only area within the United States that is only an urban area, and does not include any suburbs or rural parts. Cities tend to have younger populations and likely more digitized people. As we mentioned in the introduction, these are positively associated with cryptocurrency at a statistically significant rate.

4 Methodology

4.1 Data Cleaning and Imputation

In the data, we find that many respondents do not supply data for specific variables in our regression. We find that this is true for all the variables we include, except for the dependent variable of cryptocurrency ownership, as well as the cryptocurrency knowledge variable. As such, to avoid altering the weights for the responses we have no data for, we use imputation to create responses for any non-responses.

For the imputation, our methods depend on whether the data is discrete or continuous. For the discrete variables (cash, bank account, and online banking convenience and security, race data, education data, card adoption, mobile adoption, PayPal adoption, marital status, retirement status, female. urbanicity, and fee payments), we first calculate the mode of every variable for each US state. Then, we fill the non-response by checking the state of the respondent, and filling it with the mode for that state as already computed.

For the continuous variables (age and household income), our methods are slightly more complicated. For household income, we are interested in including the log of household income in our regression, and we have a small number of respondents reporting 0 in household income for 2022. As we cannot take the natural log of 0, we opted to also consider these as non-responses, and thus used imputation to fill the values. In the descriptive statistics above for Household Income, we see that the mean is around $87,000, which is greater than the average income in the United States of America. This is likely because on individual in the sample reported $1.75 million of income, which greatly skews the mean. As such, we opted to use the median of household income per state for the imputation. For the age variable, we see much less skewness and thus find that the mean is appropriate for the imputation. We use the same method as the other variables and fill with the mean of every US state.

Before running the regression model, we also need to transform the categorical variables to binary variables to make correct statistical analyses. The variables that we must transform are highest education, race, along with security and convenience for cash, bank accounts, and online banking. As mentioned in the descriptive statistics section, we change the highest education data from ranging from values from 1 to 16 to different levels of academic completion (elementary, middle school, high school, bachelors, and graduate). Thus, we create new columns for each of these variables. For each respondent, we determine which level is their highest educational achievement, fill in 1 for that column, and fill in 0 for the others.

For the racial data, respondents select a number from 1 to 6 to match what best fits with their racial identity. Using the provided codebook, we create new columns for the six different racial groups (White, Black, Native American, Asian, Hawaiian, and Other Race). Just like for the highest education variable, we then record 1 in the dummy column that matches the respondent's race, and 0 in all the others for that row.

Lastly, for the convenience and security variables, we employ the same method for all six variables. First, as the rankings range from 1-5, we create five new columns for each variable (30 new columns in total). Then, for each variable, we fill in 1 for the corresponding value that the respondent answers, and 0 for each others. By using this method, we create dummy variables for each level of each convenience and security variable.

4.2 Preliminary Regression Methods

4.2.1 Linear Probability Model

Now that we have a completely cleaned set of data, we are ready to construct a regression. As we are using cryptocurrency ownership as the dependent variable, which ranges from 0 to 1, we first opt for a linear probability model to determine the effects that other variables have on the probability of someone owning cryptocurrency. For our regression, we will measure the level of digitization of each respondent by the combination of card adoption, mobile adoption, and PayPal adoption variables. Thus, we will use this form of linear probability model (LPM):

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Household Income}) + \epsilon_i \tag{1}$$

where Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, and X_i is the vector of demographic variables other than household income (marital status, age, retired status, female, race, and highest level of education). To avoid any perfect collinearity in our regression, we omit the dummy variable that has the most occurrences in each category. For highest level of education we omit high school, for race we omit white, for cash convenience 5, for cash security we omit 1, for bank account convenience we omit 4, for bank account security we omit 5, for online banking convenience we omit 4, and for online banking security we omit 4.

We will also split up the variables into those we use as controls and those we aim to determine the statistical significance of. We are interested in determining the significance of card adoption, mobile adoption, PayPal adoption, log of household income, martial status, age, retirement Status, female, Black, Native American, Asian, Hawaiian or Pacific Islander, and Other Race as the variables we will interpret, and the rest as control variables.

For our regressions, we aim to see how different combinations of variables will impact the statistical significance of the results we see. Thus, we will use five different combinations of variables, which we will call specifications, to determine this. The variables that we change are referenced to as control variables in the remainder of this paper. This is done to ensure that we have a similar level of statistical significance for each of the non-control variables across the different specifications, which suggests that those variables are very important in predicting cryptocurrency ownership. First, we include all the control variables, and then we include none of them to see if there is a large effect by including the entire set. Then, we only include highest level of education to see if there is a significant effect to just including this variable. Next, we do the reverse and include all the other controls except Highest Level of Education to see if that has any opposite effect. Lastly, we include the Bank Account and Online Banking Convenience and Security variables to see if there is any confounding effect to respondent's feelings about banking on the Internet.

In our regression results, we provide the coefficients for each variable, which can be interpreted as a linear impact on the outcome variable, cryptocurrency ownership. A linear probability model is a simple way to measure how the independent variables might impact cryptocurrency ownership, but has some limitations as the probability of ownership is not restricted to be between 0 and 1.

4.2.2 Logit Model

We will also run a logit model to see if it can provide a better fit for the relationship we are trying to ascertain. The logit equation that we will run a regression on is:

$$P(Y_i = 1|\cdot) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income}))}} \tag{2}$$

where Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, and X_i is the vector of demographic variables other than household income. We omit the same binary variables as in the linear probability model for this regression, and use the same specifications as well.

In our tables of logit regression results, we present Average Marginal Effects, their standard errors, and statistical significance because they are more easy to interpret. These are calculated using software and HC1 robust standard errors. For instance, if the Average

Marginal Effect for the Card Adoption variable was 0.5, we would interpret this as those who adopt credit cards are 50% more likely to own cryptocurrency than those who do not. Clearly, this is a much more easy way to interpret our results rather than attempting to understand the logarithmic effects of movements in our $\hat{\beta}$s.

A logit model may model our data better as it restricts the outcome variable to take on values between 0 and 1. Furthermore, it is capable of assessing non-linear relationships between the independent and dependent variables, which could be possible given our data.

4.2.3 Probit Model

Lastly, we use a probit model to see if we can determine a different relationship between the regressors and the cryptocurrency ownership variable. The probit equation that we will use for the regression is:

$$P(Y_i = 1|\cdot) = \Phi(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income})) \tag{3}$$

where Φ is the cumulative distribution function (CDF) of the standard normal distribution, Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, and X_i is the vector of demographic variables other than household income. We omit the same binary variables as in the linear probability model for this regression, and use the same specifications as well.

Just like in the logit regression, we are can more easily interpret the results of the AMEs than the $\hat{\beta}$s. We interpret each AME as a linear impact on cryptocurrency ownership, rather than trying to understand the impact with the CDF function.

A probit model can be advantageous for similar reasons to a logit model, as it restricts probabilities to between 0 and 1, can handle non-linear relationships, and fits extreme probabilities better. The slight difference between a probit and logit model is that a probit model assumes a normal distribution in the error term, while the logit model assumes a logistic distribution.

4.3 ROC Curves and AUC Calculations

After finding the weighted regression results using the methods detailed above, we calculate ROC curves to understand which is the best specification for the Linear Probability, Logit, and Probit model. Specifically, we calculate the area under the ROC curve for every specification of each model, and find the specification that gives the highest amount for each model.

4.4 Control Variable Analysis

After calculating the best specification of variables for each model, we aim to interpret the control variables to understand how preferences about fiat currencies and different levels of education can impact cryptocurrency ownership. As mentioned earlier, we omit the most common variable across the ranking of convenience and security of cash, bank accounts, and online banking and also for highest level of education. Thus, the coefficients and AMEs measure the change from the base category. In the case of cash convenience, the level of 5 is omitted, so the interpretation of the cash convenience 1 variable is the movement from either side of the extreme.

To better understand the way these variables affect cryptocurrency ownership, we instead report how ownership changes through consecutive moments across each category. To this, we calculate the coefficient/AME of moving from a level of cash convenience 1 to 2, and so forth.

4.5 Multinomial Logit of Different Cryptocurrency Ownership

The next type of analysis that we are interested in is seeing how sentiments about traditional banking methods, demographics, and digitization may affect ownership of cryptocurrency differently for specific types of cryptocurrency. We will perform this analysis by creating a new variable, which will take on the value 0 if the respondent does not own any crypto, 1 if they only own Bitcoin, 2 if they only own Ethereum, 3 if they only own Litecoin, 4 if they only own Dogecoin, 5 if they only own some different crypto, and 6 if they own multiple different cryptocurrencies. We will then run the regression using this model:

$$P(Y_i = j|\cdot) = \frac{e^{\beta_0+\beta_1 D_i+\beta_2 P_i+\beta_3 X_i+\beta_4 \log(\text{Income}))}}{\sum_{k=0}^{J} e^{\beta_0+\beta_1 D_i+\beta_2 P_i+\beta_3 X_i+\beta_4 \log(\text{Income}))}} \tag{4}$$

where j ranges from 0 to 6 and denotes the different cryptocurrencies, Y_i is the binary variable of cryptocurrency ownership for each specific cryptocurrency, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, and X_i is the vector of demographic variables other than household income (marital status, age, retired status, female, race, and highest level of education).

One again, we will compute AMEs using software to provide more easily interpretable results. We will interpret the AMEs and their significance as the change in probability from the base outcome of no cryptocurrency ownership to the specific cryptocurrency in question for that variable.

4.6 Fee Payments and Financial Riskiness

As mentioned earlier, we have information about certain fees that respondents have paid in the last year. We believe that these fees represent a certain amount of financial riskiness as those who pay the fees will pay a fee to have money more available quickly. Furthermore, paying these fees suggests financial illiteracy, as those who are financially literate would know to avoid these. As fee payments will be more common among lower income individuals because of financial constraints, we include income in our future regression models to remove that effect. Therefore, we can determine if individuals with the same income will be more or less likely to own crypto if they pay fees.

We create a new variable called "risky" that has a value of 1 if the respondent has paid a Cash Advance, Late Payment, Over Limit, Bounced Check, Low Balance, or Overdraft fee in the last year, and 0 otherwise.

4.7 Connecting Crime and Survey Data

The NBIRS supplied by the FBI provides information about crime incidents in 2022, what crimes were committed, and what county they were committed in. To connect this to the survey data, we first create dummy variables for each crime, and fill in the number of times each crime occurred in each incident. Next, we create five groupings of crime which are detailed in Table 13, and sum up the total amount of crimes per grouping. Then, we group by county Federal Information Processing Standard (FIPS) code to find the count of each crime in each county. Finally, we join on the county population data from the US Census Bureau.

To connect this data to our survey data from the Understanding America Study, we use the data on rural and urban blocks within each county. We determine that if a county has over 75% urban blocks it is urban, between 25% and 50% is mixed, and below 25% is rural.

Then, we join this information onto our crime data by keying on the FIPS code. Now, we can calculate average crime statistics per rural, urban, and suburban parts of each state. We do this by grouping by state and urbanicity and sum up the total of each crime per type of region in each state along with the population. Then, we divide the count of each crime by the population (expressed in 10,000s of people).

Finally, we can join this data onto our survey data. Each respondent is given a value of 1,2, or 3 corresponding to whether they live in an urban, suburban, or rural county. As we have information about crime in each type of county in each state, we simply join on the crime statistics to the survey information. For the respondents who live in regions of states that we do not have crime statistics for (roughly 1.3% of respondents), we use the national average of the crime rate for the corresponding level of urbanicity.

4.8 Copula Fitting

To measure the dependence between whether or not a respondent is risky and if they own cryptocurrency, we estimate the following equation using multiple different copulas:[1]

$$\begin{aligned} Y_i &= (D_i + P_i + X_i + log(income))\beta + \alpha R_i + \epsilon_1, & Y &= 1[Y_i > 0] \\ R_i &= (D_i + P_i + X_i + log(income))\gamma + (log(C_i) + G_i)\delta + \epsilon_2, & R &= 1[R_i > 0] \\ \text{with } \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} &\sim F(\epsilon_1, \epsilon_2) \end{aligned} \tag{5}$$

where Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, X_i is the vector of demographic variables other than household income, C_i is the vector of crimes variables other than gambling, bribery, and corruption, G_i is Gambling, Bribery, and Corruption, and R_i is whether or not a respondent has paid one of the aforementioned fees in the last year. Then, we calculate the Average Treatment Effect (ATE) of the risk variable using this formula:

[1] Because there are some respondents who are matched up with areas that have no Gambling, Bribery, and Corruption, we cannot use a log transformation for this variable. Additionally, we do not use sampling weights for the copula or ATE calculation.

$$\begin{aligned}\text{ATE}_R = \ & \Pr\left(Y = 1 \mid D_i + P_i + X_i + \log(\text{income})\right)\big|_{R=1} \\ & - \Pr\left(Y = 1 \mid D_i + P_i + X_i + \log(\text{income})\right)\big|_{R=0}\end{aligned} \tag{6}$$

4.9 Other Instrument Variable Tests

4.9.1 Biprobit

To confirm our results from the copula fitting with the crime variables as instrument variables, we estimate a Biprobit model:

$$\begin{aligned} Y_i &= (D_i + P_i + X_i + log(income))\beta + \alpha y_2 + \epsilon_1, & Y = 1[Y_i > 0] \\ R_i &= (D_i + P_i + X_i + log(income))\gamma + (log(C_i) + G_i)\delta + \epsilon_2, & R = 1[R_i > 0] \\ \text{with } & \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim F\left(\epsilon_1, \epsilon_2\right) \end{aligned} \tag{7}$$

$$\text{ATE}_R = \hat{P}(Y = 1 \mid R = 1) - \hat{P}(Y = 1 \mid R = 0) \tag{8}$$

where Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, X_i is the vector of demographic variables other than household income, C_i is the vector of crimes variables other than gambling, bribery, and corruption, G_i is Gambling, Bribery, and Corruption, and R_i is whether or not a respondent has paid one of the aforementioned fees in the last year. We use weights in this method, unlike in the copulae.

4.9.2 Two Stage Residual Inclusion

We also use the Two Stage Residual Inclusion approach for added robustness in our results:

$$P(R_i = 1|\cdot) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income}) + \beta_5 log(C_i) + \beta_6 G_i)}} \tag{9}$$

$$\epsilon_i = R_i - \hat{R}_i \tag{10}$$

$$P(Y_i = 1|\cdot) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income}) + \beta_5 \hat{R}_i + \beta_6 \epsilon_i)}} \tag{11}$$

$$\text{ATE}_R = \hat{P}(Y = 1 \mid R = 1) - \hat{P}(Y = 1 \mid R = 0) \tag{12}$$

where Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, X_i is the vector of demographic variables other than household income, C_i is the vector of crimes variables other than gambling, bribery, and corruption, G_i is Gambling, Bribery, and Corruption, and R_i is whether or not a respondent has paid one of the aforementioned fees in the last year. We use weights in this method, unlike in the copulae.

4.10 Impact of Crime Levels

After performing the data joining mentioned earlier, we are able to see the impact that county-level crime has on ownership of cryptocurrency to see if there is a connection. We first estimate a logit equation:

$$P(Y_i = 1|\cdot) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income}) + \beta_5 log(C_i) + \beta_6 G_i + \beta_7 R_i)}} \tag{13}$$

and then a probit equation:

$$P(Y_i = 1|\cdot) = \Phi(\beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 X_i + \beta_4 \log(\text{Income}) + \beta_5 \log(C_i) + \beta_6 G_i + \beta_7 R_i) \tag{14}$$

where Φ is the CDF of the standard normal, Y_i is the binary variable of cryptocurrency ownership, D_i is the vector of digitization variables, P_i is the vector of convenience and security for different traditional banking methods, X_i is the vector of demographic variables other than household income, C_i is the vector of crimes variables other than government regulatory offenses, G_i is Government Regulatory Offenses, and R_i is whether or not a respondent has paid one of the aforementioned fees in the last year. Then, we calculate AMEs to more easily interpret the results.

5 Results

5.1 Preliminary Regression Results

5.1.1 Linear Probability Model

Table 5 and Table 6 contain our results for the unweighted LPM and weighted LPM, respectively. Although we know that certain populations are over sampled in our population, we reported unweighted results for extra robustness. However, as the weights make the survey much more representative of the actual United States, we focus our analysis on the weighted results.

To ensure robustness of our results, we compare the statistical significance of our variables across all five specifications. Here, we see that Card Adoption, Mobile Adoption, Paypal Adoption, Household Income, and Asian are all statistically significantly positive predictors of cryptocurrency ownership across all five specifications at minimally 90% confidence. Age, Hawaiian, and Female are the two only statistically significant negative relationships with cryptocurrency ownership, which both occur at a 99% confidence level. Over all the statistically significant variables, only Household Income varies in significance level across the specifications, and it is an increase from the full variable regression. Other Race varies from being significant at a 90% level to not being significant at all, so we do not make a conclusion about its impact on cryptocurrency ownership.

One important note to make regarding our LPM results is that the model predicts negative probabilities of owning cryptocurrency, meaning we should be skeptical of these results as it is not a perfect fit for our data.

5.1.2 Logit Model

We report our logit regression results in Table 7 and Table 8. Again, we will focus on the weighted results, which show that all the digitization variables are positively significant at a 99% level, with Age, Female, and Hawaiian being negatively significant at a 99% level across all five specifications. Household Income is positively significant at minimally a 90% level, and Asian at a 99% level. As we do not have issues with unbounded probabilities in a logit model, we can be confident that these results are reliable.

5.1.3 Probit Model

To conclude our preliminary results, we report our logit regression results in Table 9 and Table 10. Here, we see a similar story to the logit model, with the digitization variables and Asian all being positively correlated at the 99% level, and Age, Female and Hawaiian being negatively related at the 99% level. One minor difference is that Household Income is not signification across all specifications, so we do not make any conclusions about this relationship. Lastly, Other Race is positively significant at the 90% level.

5.2 ROC Curves

After fitting the weighted regressions, we use the predicted probabilities to calculate ROC curves. These results are demonstrated in Figure 16, Figure 17, and Figure 18. Here, we see that the highest Area Under the Curve (AUC) for the LPM comes from specification 1. Specification 1 is also the highest AUC for the other two models, suggesting that it is the best fit for our data across all the models. This is not a surprising result considering it includes the most amount of variables of all the specifications.

5.3 Best Specification for Each Model

We include the weighted results for the best specification of each model in Table 11. Even though these are all the same specification, we see that using different models generates different coefficients, standard errors, and levels of statistical significance for multiple variables. We see that the digitization variables and Asian are positive predictors at the 99% level across all three models. Age, Female, and Hawaiian are all negatively related at the 99% level. Other Race is positively significant at the 90% level. None of the all variables have a level of significance across all three models, so we make no conclusion about their relation to cryptocurrency ownership.

5.4 Control Variables Analysis

Now, we present the findings from out control variables to see how sentiments on traditional banking and levels of education affect cryptocurrency ownership. We provide Table 12 to demonstrate these effects. The coefficients/AMEs represent a change from one level to another, to give a more complete understanding of how the control variables affect cryptocurrency ownership.

For the LPM, a movement from online banking security 2 to 3 is positively significant, from middle to high school is positive, from high school to bachelor's is positive, and from bachelor's to graduate is negative.

For the logit and probit models, we see that there are no instances of statistical significance in moving across sentiments about traditional banking. For education levels, we see that moving from elementary to middle has a positive effect in the logit model, and from middle school to high school is positive in the probit model. In both of the models, we see that moving from high school to bachelor's is a positive significant effect.

Here, we see that there is no evidence to suggest that those who own cryptocurrency have significantly different sentiments on traditional banking than those who not. The only robust result from highest levels of education is that moving from high school to bachelor's degree has a positive impact on ownership.

5.5 Multinomial Logit By Different Cryptocurrency

As owners of different crypto may have different preferences, we report Multinomial logit results for different cryptocurrencies.

Figure 19 shows the AME of moving from no ownership to owning specifically Bitcoin. Here, we see that Black, Card Adopt, Female, Household Income, Married, Mobile Adopt, PayPal Adopt, Other Race, and Retired are positive predictors of Bitcoin ownership. Age, Asian, Hawaiian, and Native American are negative predictors.

Figure 20 shows the AME of moving from no ownership to owning specifically Ethereum. Here, we see that Asian, Card Adopt, Household Income, Married, and Other Race are positive predictors of Bitcoin ownership. Age, Asian, Hawaiian, and Native American are negative predictors.

Figure 21 shows the AME of moving from no ownership to owning specifically Litecoin. We see that there are no variables that are positively associated with Litecoin ownership. Only age is negatively associated with Litecoin ownership.

Figure 22 shows the AME of moving from no ownership to owning specifically Dogecoin. Here, wee see that Age, Asian, Black, Female, Hawaiian, Household Income, Native American, and PayPal Adopt are negatively associated with Dogecoin ownership at the 95% level. Card Adopt, Married, Mobile Adopt, and Other Race are positively associated at the 95% confidence level.

Figure 23 shows the AME of moving from no ownership to owning specifically some other cryptocurrency. Here, we see that Card Adopt, Married, Mobile Adopt, and Other Race are positively associated. Asian, Black, Female, Hawaiian, Household Income, Native American, and PayPal Adopt are negatively associated.

Figure 24 shows the AME of moving from no ownership to owning multiple cryptocurrencies. Asian, Black, Card Adopt, Household Income, Mobile Adopt, PayPal Adopt, and Other Race are positively associated. Female, Hawaiian, Native American, and Retired are negatively assosicated.

5.6 Copula Fitting

Table 1: Copula ATEs

Copula	ATE	SE	Z	P-Value	95% CI
Plackett	0.051	0.016	3.17	0.002	(0.020,0.083)
Frank	0.051	0.016	3.24	0.001	(0.020,0.082)
AMH	0.021	0.005	4.20	0.000	(0.011,0.030)

Note: Calculated without sampling weights

First, we analyze the results of the ATE of the risky variable upon cryptocurrency ownership. In all the copulae we use, we see that the ATE is positively statistically significant. This suggests that after controlling for the covariates and endogeneity, paying one of the aforementioned fees results in a higher likelihood of cryptocurrency ownership.

Table 2: Copula Comparison

Copula	θ	τ	Wald Test P-Value	Log-Likelihood	AIC
Plackett	0.557	-	0.003	-3443.1521	7046.304
Frank	-1.173	-0.129	0.026	-3443.1082	7046.216
AMH	-0.558	-0.110	0.011	-3443.0758	7046.152

Note: No τ for Plackett copula, calculated without sampling weights

Next, we evaluate how well each of the copulae fit our data, and what the parameters tell us about the dependence structures between cryptocurrency ownership and the "risky" variable.

$\theta < 1$ in the Plackett model output suggests a slight negative relationship between ownership and the risky variable, and the Wald Test confirms that this relationship is statistically significant.

In the Frank copula, the θ value indicates a negative dependence with moderate strength, and the Wald Test also confirms that the value is statistically significant. The value of τ

suggests a negative rank correlation, meaning that as the rank of risky increases, the rank of ownership decreases.

For the AMH copula, the value for θ suggests a slight negative relationship between ownership and the risky variable. Once again, the low value of the Wald Test P-Value confirms that this result is statistically significant.

In comparing the three copulae, we see that the magnitude of the log-likelihood is lowest for the AMH copula, indicating that it has the best fit for our data. As all the copulae use the same parameters, the AIC calculation will not alter the hierarchy of ordering, which is that the AMH is best, then Frank, and lastly Plackett.

5.7 Other Instrument Variable Tests

Table 3: Other IV Calculations

	ATE	SE	t	P-Value	95% CI
Biprobit	0.037	0.007	5.16	0.000	(0.023,0.051)
2SRI	0.048	0.016	3.02	0.003	(0.017,0.079)

Note: Calculated with sampling weights

Here, we include our results for the ATE of the risky variable in the Biprobit and Two Stage Residual Inclusion methods. We see quite similar results to the ATE calculations as in the copulae, with slightly different magnitude. Both methods demonstrate that the ATE is statistically significant in the positive direction, meaning that conditional on the covariates, the risky variable increases the likelihood of cryptocurrency ownership.

5.8 Crime Level Analysis

To determine how crime rates impact cryptocurrency ownership, we analyze the AMEs and their statistical significance from the logit and probit regressions included in Table 14. Here, we see that only two of the crime variables are significant. Violent crime rates have a positive effect and theft related crime rates have a negative effect, both at the 99% level. Furthermore, we see that after adding these variables to the regression, we maintain the same level of statistical significance for all the variables we included in our best specification models.

It is also interesting to see that the risky variable is not statistically significant in this specification. It is likely that its correlation with the other predictors reduces its impact on ownership, so we can see the effect in the ATE calculation, but not here.

6 Conclusion

From this research we can better understand the motivators for cryptocurrency ownership, and therefore suggest improvements to regulatory policy.

In our preliminary regression analysis, we see that adoption of financial technology is positively associated with cryptocurrency ownership, suggesting that cryptocurrency is a complement for existing financial technology, not a substitute. If this is the case, regulators should consider how to ensure using these financial mediums to purchase cryptocurrency are secure. For instance, the Federal Depository Insurance Corporation could consider extending its protections to PayPal, meaning that cryptocurrency investors could be better protected.

We also see in our preliminary regression results that cryptocurrency is popular among certain demographics. The only significant difference in education levels comes from moving from high school to Bachelor's graduates. As Bachelor's graduates will be more investment savvy, regulators should consider making cryptocurrency platform disclose fees and other risks so that investors can make informed decisions. Certain demographics are associated with higher or lower likelihood to own cryptocurrency, perhaps because of a lack of knowledge or understanding. As such, information dispersion could be targeted at those less likely to own cryptocurrency to make crypto more equitable.

After fitting the best specification for each model, we find that the measures of convenience and security for traditional banking methods has so significant impact on cryptocurrency ownership. This indicates that owners of cryptocurrency do not seek it out as an alternative to existing banking, but as an investment. In the United States, regulation of investment vehicles is strict, so classifying cryptocurrencies as an investment would give regulators the opportunity to better protect investors.

From the multinomial logit of different cryptocurrencies, we see that the characteristics of investors varies widely for different cryptocurrencies. For instance, we see that women are negatively associated with ownership of all cryptocurrencies except Bitcoin, where there is a positive association. Evidently, women have some strong preference towards Bitcoin, perhaps because it is the most established and popular cryptocurrency. We also see that specific coins are popular among certain racial groups, perhaps because of network effects. In totality, this analysis suggests that a one size fits all approach to cryptocurrency regulation is not appropriate as different coins have different investors.

Next, we find from our copulae, BiProbit, and Two Stage Residual Inclusion models that paying a bounced check, cash advance, late payment, low balance, over limit, or overdraft fee in the last year has a positive ATE on cryptocurrency ownership. Paying these fees indicates some level of financial riskiness or illiteracy, hence why we name the variable “risky”. Such an outcome signals that those who are financially illiterate are positively associated with owning cryptocurrency. For regulators, this will be an important finding as it suggests that cryptocurrency investment could be driven by a lack of financial understanding. Furthermore, it indicates that these individuals looks towards crypto as a lottery-like investment.

As such, regulators should increase protections against rug pulls and other scams that prey on the financially illiterate.

Lastly, we find that crime rates in the region of the respondent have a significant effect on ownership. Specifically, theft related crimes are positively associated, and violent crimes have a negative effect. Cryptocurrency is a helpful tool for criminals to transfer funds with, which our analysis confirms. To increase the legitimacy of cryptocurrency, regulators should place emphasis on developing methods to detect potential crime related transactions so they can intervene. Violent crime has been proven to increase risk aversion among individuals in the area, so it is not a surprise to see this negative relationship (Brown et al., 2017). To solve this issue, it would be prudent for regulators to soothe this aversion with additional security measures and fraud protection.

The conclusions drawn from this analysis aim to aid regulators in understanding what drives cryptocurrency ownership, and what problems regulation needs to solve.

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Appendix

Data Dictionary

Table 4: Data Dictionary

Variable	Meaning
Ownership	1 if owns a cryptocurrency, 0 otherwise
Knowledge	1 if heard of cryptocurrency, 0 otherwise
Card Adoption	1 if has a payment card, 0 otherwise
Mobile Adoption	1 if made a mobile payment in the last year, 0 otherwise
PayPal Adoption	1 if used PayPal in the last year, 0 otherwise
Household Income	household income for 2022 in thousands of USD
Marital Status	1 if married, 0 if otherwise
Age	respondent's age in years
Retirement Status	1 if retired, 0 if otherwise
Female	1 if female, 0 if otherwise
Black	1 if Black, 0 if otherwise
Native American	1 if Native American, 0 if otherwise
Asian	1 if Asian, 0 if otherwise
Hawaiian or Pacific Islander	1 if Hawaiian or Pacific Islander, 0 if otherwise
Other Race	1 if none of the above races or mixed race, 0 otherwise
Highest Level of Education	highest level of education achieved
Cash Convenience	convenience of cash on a scale of 1 to 5
Cash Security	security of cash on a scale of 1 to 5
Bank Account Convenience	convenience of bank accounts on a scale of 1 to 5
Bank Account Security	security of bank accounts on a scale of 1 to 5
Online Banking Convenience	convenience of online banking on a scale of 1 to 5
Online Banking Security	security of online banking on a scale of 1 to 5
Urban Category	1 if in a rural county, 2 if in mixed, 3 if in urban
Bitcoin Ownership	1 if owns Bitcoin, 0 otherwise
Ethereum Ownership	1 if owns Ethereum, 0 otherwise
Litecoin Ownership	1 if owns Litecoin, 0 otherwise
Dogecoin Ownership	1 if owns Dogecoin, 0 otherwise
Other Crypto Ownership	1 if owns Other Crypto, 0 otherwise
Cash Advance Fee	1 if paid a cash advance fee in the last year, 0 otherwise
Late Payment Fee	1 if paid a late payment fee in the last year, 0 otherwise
Over Limit Fee	1 if paid an over limit fee in the last year, 0 otherwise
Bounced Check Fee	1 if paid a bounced check fee in the last year, 0 otherwise
Low Balance Fee	1 if paid a low balance fee in the last year, 0 otherwise
Overdraft Fee	1 if paid an overdraft fee in the last year, 0 otherwise

Preliminary Results

LPM Results

Table 5: Unweighted Linear Probability Model Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.044***	0.047***	0.042***	0.049***	0.048***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Mobile Adoption	0.039***	0.043***	0.041***	0.040***	0.041***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
PayPal Adoption	0.049***	0.051***	0.050***	0.050***	0.050***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Household Income (Log)	0.006**	0.008***	0.007***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Marital Status	−0.001	−0.002	−0.002	−0.001	−0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retired Status	−0.009	−0.005	−0.007	−0.008	−0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Female	−0.078***	−0.080***	−0.079***	−0.079***	−0.079***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Black	0.020	0.019	0.020	0.019	0.018
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Native American	0.015	0.010	0.010	0.014	0.012
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Asian	0.063***	0.066***	0.065***	0.063***	0.062***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Hawaiian	−0.007	−0.003	−0.005	−0.004	−0.002
	(0.068)	(0.070)	(0.070)	(0.068)	(0.068)
Other Race	0.044*	0.044*	0.045**	0.043*	0.042*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

Table 6: Weighted Linear Probability Model Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.059***	0.056***	0.050***	0.064***	0.063***
	(0.018)	(0.015)	(0.016)	(0.017)	(0.017)
Mobile Adoption	0.044***	0.052***	0.048***	0.047***	0.048***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
PayPal Adoption	0.057***	0.062***	0.060***	0.059***	0.061***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Household Income (Log)	0.009**	0.012***	0.010**	0.011***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Marital Status	−0.002	−0.001	−0.001	−0.003	−0.001
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Retired Status	−0.005	0.0003	−0.003	−0.003	−0.002
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Female	−0.081***	−0.080***	−0.081***	−0.080***	−0.080***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.027	0.024	0.024	0.027	0.025
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Native American	−0.035	−0.037	−0.037	−0.035	−0.030
	(0.037)	(0.036)	(0.035)	(0.038)	(0.038)
Asian	0.094***	0.104***	0.097***	0.098***	0.102***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Hawaiian	−0.146***	−0.159***	−0.154***	−0.149***	−0.155***
	(0.033)	(0.034)	(0.032)	(0.034)	(0.036)
Other Race	0.052*	0.054*	0.052	0.054*	0.053*
	(0.031)	(0.032)	(0.032)	(0.031)	(0.031)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

Logit Results

Table 7: Unweighted Logit Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.886***	0.905***	0.894***	0.897***	0.900***
	(0.044)	(0.045)	(0.044)	(0.044)	(0.045)
Mobile Adoption	0.049***	0.053***	0.050***	0.051***	0.051***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
PayPal Adoption	0.046***	0.048***	0.046***	0.047***	0.047***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Household Income (Log)	0.011**	0.013***	0.011**	0.012**	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Marital Status	0.006	0.004	0.005	0.005	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retired Status	-0.026	-0.023	-0.024	-0.025	-0.026
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Female	-0.073***	-0.075***	-0.074***	-0.074***	-0.074***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Black	0.025*	0.025*	0.026*	0.024	0.023
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Native American	0.019	0.015	0.015	0.019	0.017
	(0.032)	(0.033)	(0.033)	(0.032)	(0.032)
Asian	0.039***	0.038***	0.039***	0.037***	0.035***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Hawaiian	-0.016	-0.017	-0.015	-0.017	-0.015
	(0.084)	(0.089)	(0.087)	(0.086)	(0.087)
Other Race	0.035**	0.036**	0.036**	0.034**	0.033**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

Table 8: Weighted Logit Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.922***	0.909***	0.927***	0.907***	0.908***
	(0.060)	(0.058)	(0.059)	(0.059)	(0.058)
Mobile Adoption	0.049***	0.054***	0.052***	0.050***	0.051***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
PayPal Adoption	0.044***	0.047***	0.046***	0.044***	0.046***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Household Income (Log)	0.014*	0.018**	0.015*	0.016**	0.017**
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Marital Status	0.007	0.007	0.008	0.006	0.008
	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retired Status	-0.024	-0.020	-0.023	-0.021	-0.020
	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)
Female	-0.068***	-0.066***	-0.069***	-0.066***	-0.067***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Black	0.027	0.027	0.027	0.027	0.026
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Native American	-0.031	-0.034	-0.035	-0.03	-0.026
	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Asian	0.051***	0.051***	0.051***	0.050***	0.052***
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
Hawaiian	-0.338***	-0.340***	-0.344***	-0.335***	-0.339***
	(0.083)	(0.081)	(0.083)	(0.081)	(0.082)
Other Race	0.037**	0.037**	0.037**	0.037**	0.036**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

Probit Results

Table 9: Unweighted Probit Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.499***	0.51***	0.509***	0.504***	0.507***
	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)
Mobile Adoption	0.045***	0.049***	0.047***	0.047***	0.047***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
PayPal Adoption	0.045***	0.047***	0.046***	0.046***	0.046***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Household Income (Log)	0.009**	0.011**	0.009**	0.010**	0.011**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Marital Status	0.007	0.006	0.006	0.006	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retired Status	-0.019	-0.018	-0.018	-0.018	-0.019
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Female	-0.071***	-0.073***	-0.072***	-0.072***	-0.072***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Black	0.026*	0.027*	0.028*	0.025*	0.025*
	(0.014)	(0.015)	(0.014)	(0.015)	(0.015)
Native American	0.016	0.015	0.014	0.017	0.016
	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)
Asian	0.038***	0.039***	0.039***	0.037***	0.035**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Hawaiian	-0.005	0.004	0.004	-0.005	-0.001
	(0.08)	(0.087)	(0.084)	(0.082)	(0.083)
Other Race	0.037**	0.038**	0.038**	0.037**	0.036**
	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

Table 10: Weighted Probit Comparison

	(1)	(2)	(3)	(4)	(5)
Card Adoption	0.524***	0.509***	0.523***	0.513***	0.514***
	(0.036)	(0.033)	(0.035)	(0.034)	(0.034)
Mobile Adoption	0.048***	0.054***	0.051***	0.050***	0.051***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)
PayPal Adoption	0.044***	0.047***	0.046***	0.045***	0.046***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)
Household Income (Log)	0.012	0.015*	0.012	0.014**	0.014*
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Marital Status	0.009	0.010	0.011	0.009	0.010
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retired Status	-0.015	-0.013	-0.015	-0.013	-0.013
	(0.021)	(0.02)	(0.021)	(0.020)	(0.020)
Female	-0.069***	-0.066***	-0.069***	-0.066***	-0.066***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Black	0.029	0.029	0.029	0.030*	0.029
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Native American	-0.035	-0.036	-0.039	-0.031	-0.026
	(0.043)	(0.043)	(0.043)	(0.044)	(0.045)
Asian	0.052***	0.054***	0.052***	0.052***	0.054***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Hawaiian	-0.264***	-0.272***	-0.272***	-0.262***	-0.27***
	(0.056)	(0.055)	(0.056)	(0.055)	(0.057)
Other Race	0.039**	0.039**	0.038**	0.039**	0.038**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Highest Level of Education	✓		✓		
Cash Convenience	✓			✓	
Cash Security	✓			✓	
Bank Account Convenience	✓			✓	✓
Bank Account Security	✓			✓	✓
Online Banking Convenience	✓			✓	✓
Online Banking Security	✓			✓	✓
Observations	4,719	4,719	4,719	4,719	4,719

Note: HC1 robust standard errors reported in parentheses, constant used but excluded from results, *p<0.1; **p<0.05; ***p<0.01

ROC Curve Results

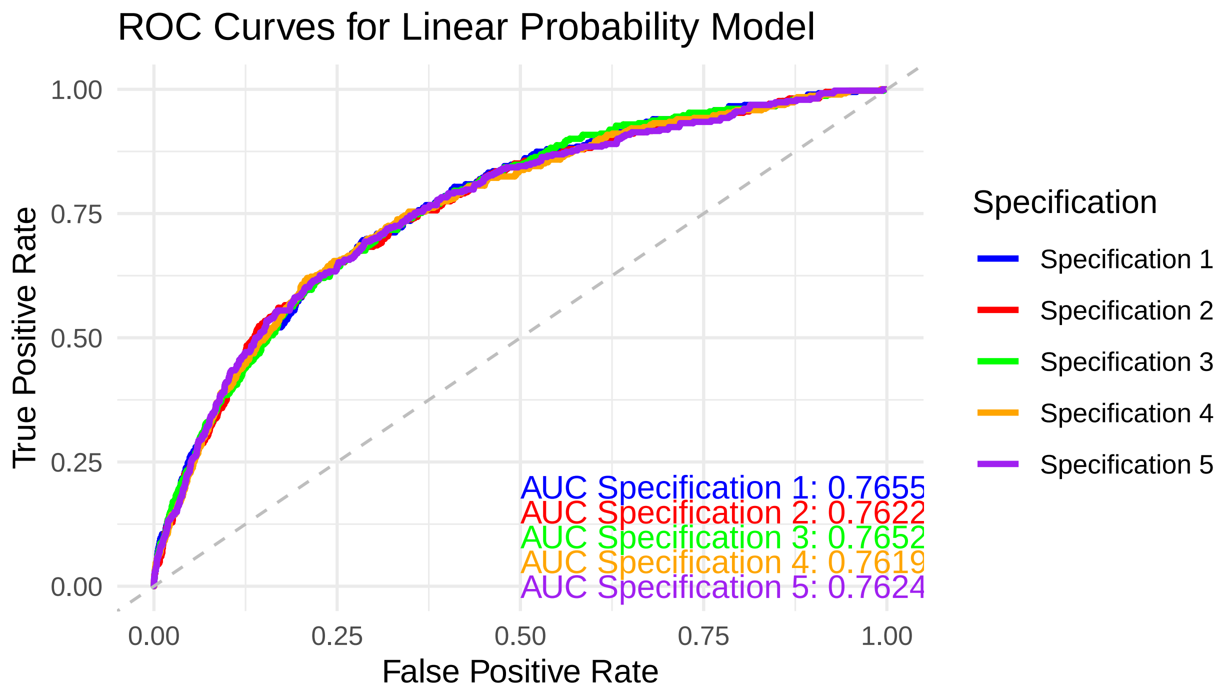

Figure 16: Weighted LPM ROC Curve

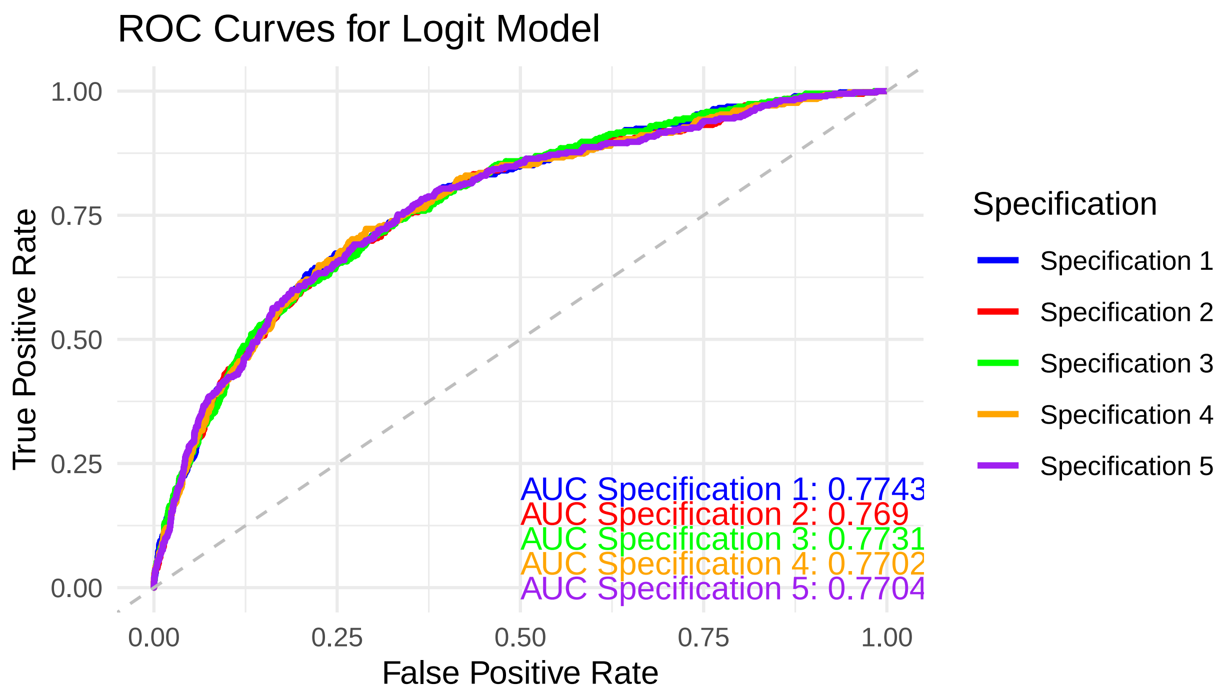

Figure 17: Weighted Logit ROC Curve

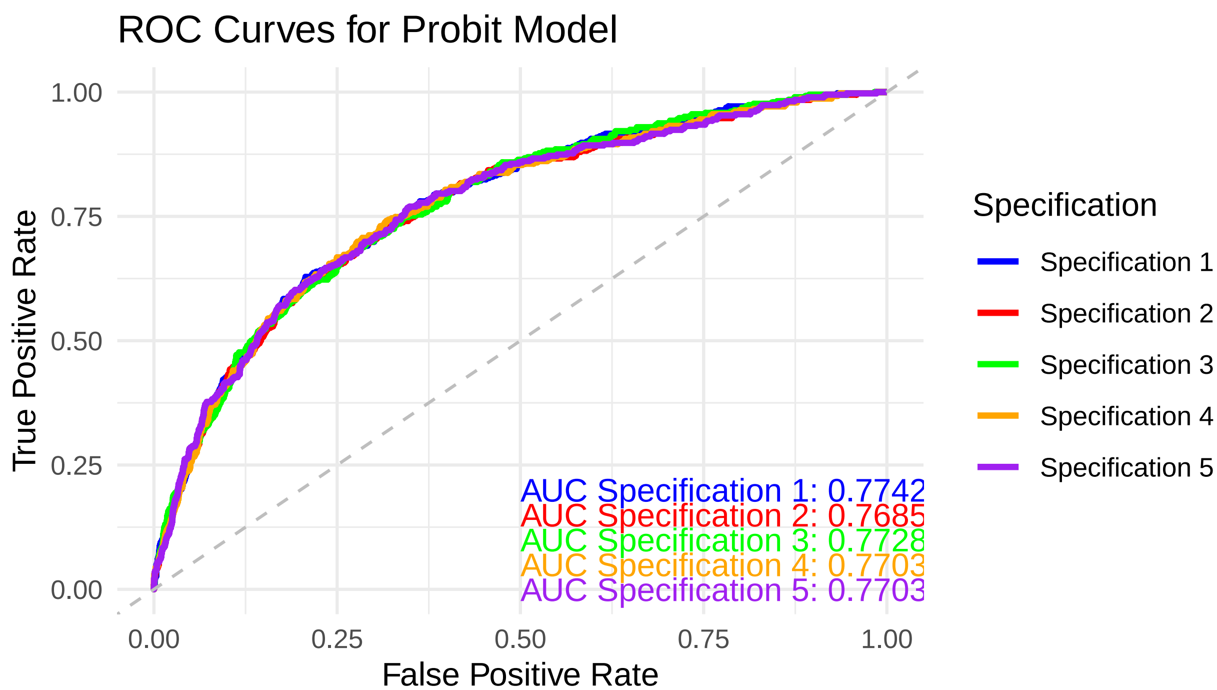

Figure 18: Weighted Probit ROC Curve

Best Specification Results

Table 11: Highest AUC Specification for Each Model (Weighted)

	(Linear Probability)	(Logit)	(Probit)
Card Adoption	0.059***	0.922***	0.524***
	(0.018)	(0.060)	(0.036)
Mobile Adoption	0.044***	0.049***	0.048***
	(0.012)	(0.015)	(0.014)
PayPal Adoption	0.057***	0.044***	0.044***
	(0.014)	(0.011)	(0.011)
Household Income (Log)	0.009**	0.014*	0.012
	(0.004)	(0.008)	(0.007)
Marital Status	−0.002	0.007	0.009
	(0.013)	(0.012)	(0.012)
Age	−0.002***	−0.002***	−0.002***
	(0.0001)	(0.000)	(0.000)
Retired Status	−0.005	−0.024	−0.015
	(0.013)	(0.023)	(0.021)
Female	−0.081***	−0.068***	−0.069***
	(0.012)	(0.010)	(0.010)
Black	0.027	0.027	0.029
	(0.019)	(0.018)	(0.018)
Native American	−0.035	−0.031	−0.035
	(0.037)	(0.047)	(0.043)
Asian	0.094***	0.051***	0.052***
	(0.035)	(0.016)	(0.017)
Hawaiian	−0.146***	−0.338***	−0.264***
	(0.033)	(0.083)	(0.056)
Other Race	0.052*	0.037**	0.039**
	(0.031)	(0.017)	(0.018)
Highest Level of Education	✓	✓	✓
Cash Convenience	✓	✓	✓
Cash Security	✓	✓	✓
Bank Account Convenience	✓	✓	✓
Bank Account Security	✓	✓	✓
Online Banking Convenience	✓	✓	✓
Online Banking Security	✓	✓	✓
Observations	4,719	4,719	4,719
Note:			*p<0.1; **p<0.05; ***p<0.01

Control Variable Results

Table 12: Categorical Variable Analysis

	LPM	Logit	Probit
Cash Conv. (2) - Cash Conv. (1)	0.041	0.015	0.023
	(0.049)	(0.071)	(0.072)
Cash Conv. (3) - Cash Conv. (2)	-0.030	-0.013	-0.020
	(0.036)	(0.125)	(0.126)
Cash Conv. (4) - Cash Conv. (3)	-0.009	-0.002	-0.003
	(0.025)	(0.205)	(0.205)
Cash Conv. (5) - Cash Conv. (4)	-0.005	-0.006	-0.002
	(0.016)	(0.014)	(0.014)
Cash Secur. (2) - Cash Secur. (1)	-0.044**	-0.032	-0.030
	(0.021)	(0.020)	(0.020)
Cash Secur. (3) - Cash Secur. (2)	0.009	0.003	-0.002
	(0.027)	(0.126)	(0.127)
Cash Secur. (4) - Cash Secur. (3)	0.021	0.019	0.024
	(0.031)	(0.118)	(0.118)
Cash Secur. (5) - Cash Secur. (4)	-0.016	-0.016	-0.021
	(0.026)	(0.179)	(0.179)
Online Banking Conv. (2) - Online Banking Conv. (1)	0.037	0.039	0.046
	(0.061)	(0.060)	(0.062)
Online Banking Conv. (3) - Online Banking Conv. (2)	-0.025	-0.022	-0.020
	(0.043)	(0.097)	(0.098)
Online Banking Conv. (4) - Online Banking Conv. (3)	0.004	0.005	0.004
	(0.021)	(0.303)	(0.303)
Online Banking Conv. (5) - Online Banking Conv. (4)	0.005	0.007	0.007
	(0.014)	(0.012)	(0.012)
Online Banking Secur. (2) - Online Banking Secur. (1)	0.010	0.005	0.006
	(0.033)	(0.108)	(0.108)
Online Banking Secur. (3) - Online Banking Secur. (2)	0.050*	0.045	0.046
	(0.030)	(0.155)	(0.155)

	LPM	Logit	Probit
Online Banking Secur. (4) - Online Banking Secur. (3)	-0.031	-0.022	-0.027
	(0.027)	(0.020)	(0.021)
Online Banking Secur. (5) - Online Banking Secur. (4)	0.030	0.012	0.015
	(0.034)	(0.022)	(0.023)
Bank Acc. Conv. (2) - Bank Acc. Conv. (1)	-0.060	-0.033	-0.037
	(0.039)	(0.133)	(0.133)
Bank Acc. Conv. (3) - Bank Acc. Conv. (2)	-0.002	-0.004	-0.006
	(0.021)	(0.295)	(0.295)
Bank Acc. Conv. (4) - Bank Acc. Conv. (3)	0.005	0.007	0.008
	(0.016)	(0.014)	(0.014)
Bank Acc. Conv. (5) - Bank Acc. Conv. (4)	0.001	0.001	0.002
	(0.025)	(0.022)	(0.022)
Bank Acc. Secur. (2) - Bank Acc. Secur. (1)	0.005	0.000	0.001
	(0.026)	(0.255)	(0.255)
Bank Acc. Secur. (3) - Bank Acc. Secur. (2)	-0.019	-0.020	-0.020
	(0.023)	(0.249)	(0.249)
Bank Acc. Secur. (4) - Bank Acc. Secur. (3)	0.027	0.026	0.028
	(0.022)	(0.019)	(0.019)
Bank Acc. Secur. (5) - Bank Acc. Secur. (4)	-0.053	-0.033	-0.033
	(0.039)	(0.030)	(0.031)
Middle School - Elementary School	-0.025	0.772***	0.379
	(0.029)	(0.085)	(0.065)
High School - Middle School	0.034**	0.082	0.080*
	(0.015)	(0.052)	(0.043)
Bachelor's Degree - High School	0.044**	0.024**	0.026**
	(0.018)	(0.012)	(0.012)
Graduate Degree - Bachelor's Degree	-0.044**	-0.028	-0.029
	(0.022)	(0.317)	(0.317)

Multinomial Logit by Different Cryptocurrency

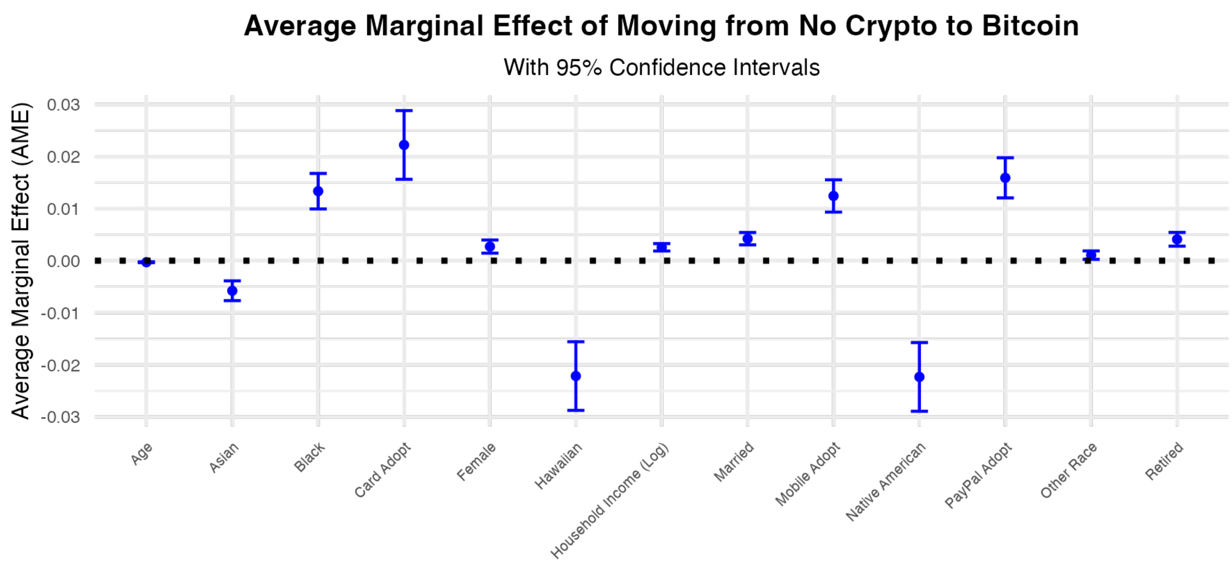

Figure 19: AME of Bitcoin Ownership

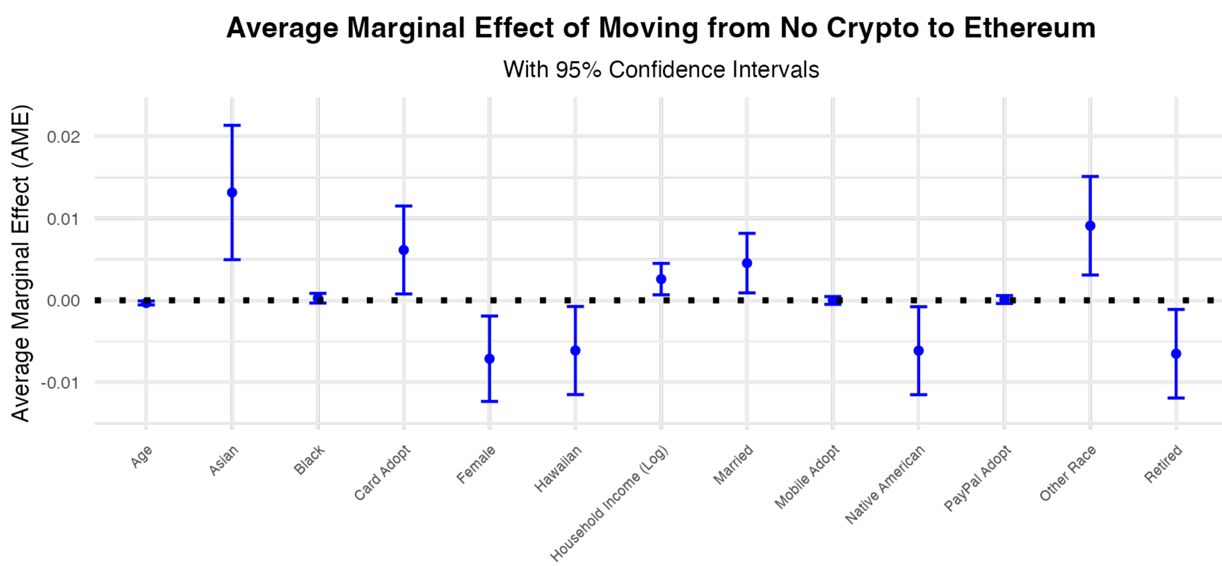

Figure 20: AME of Ethereum Ownership

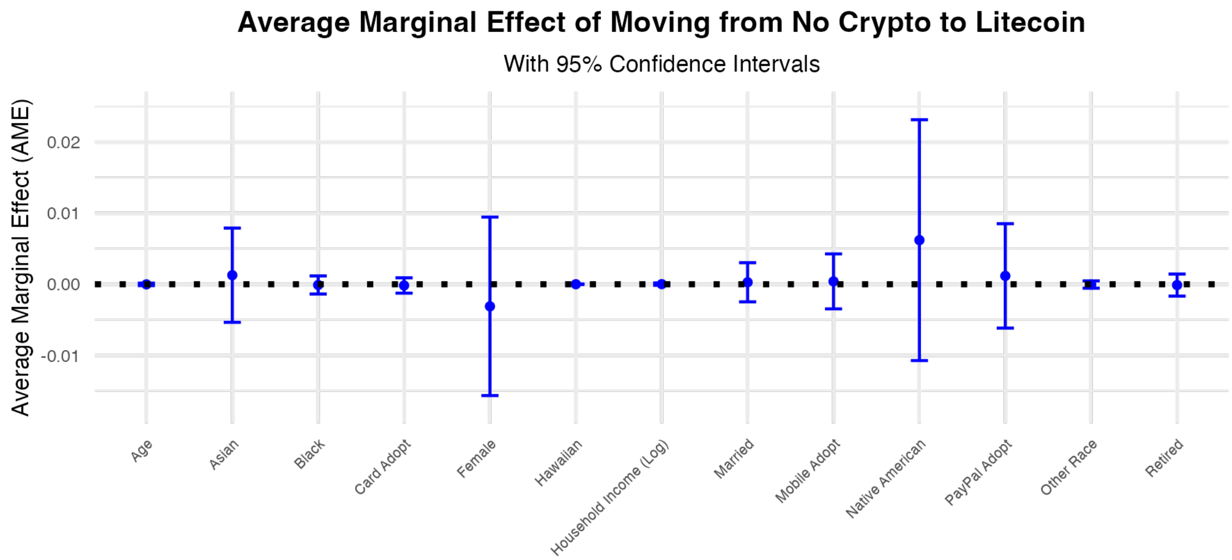

Figure 21: AME of Litecoin Ownership

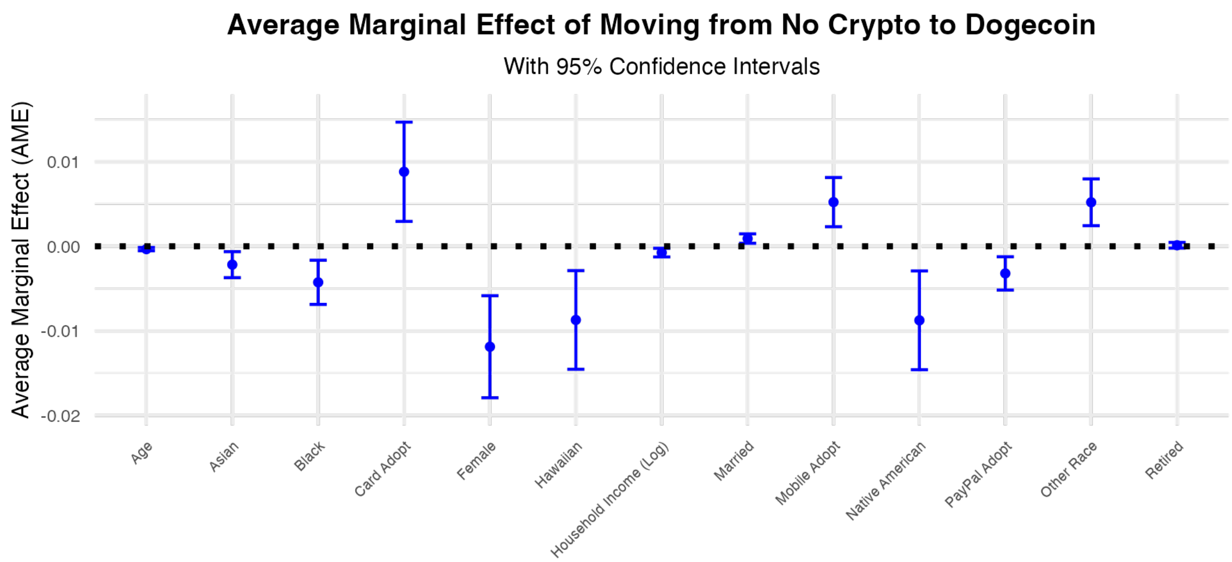

Figure 22: AME of Dogecoin Ownership

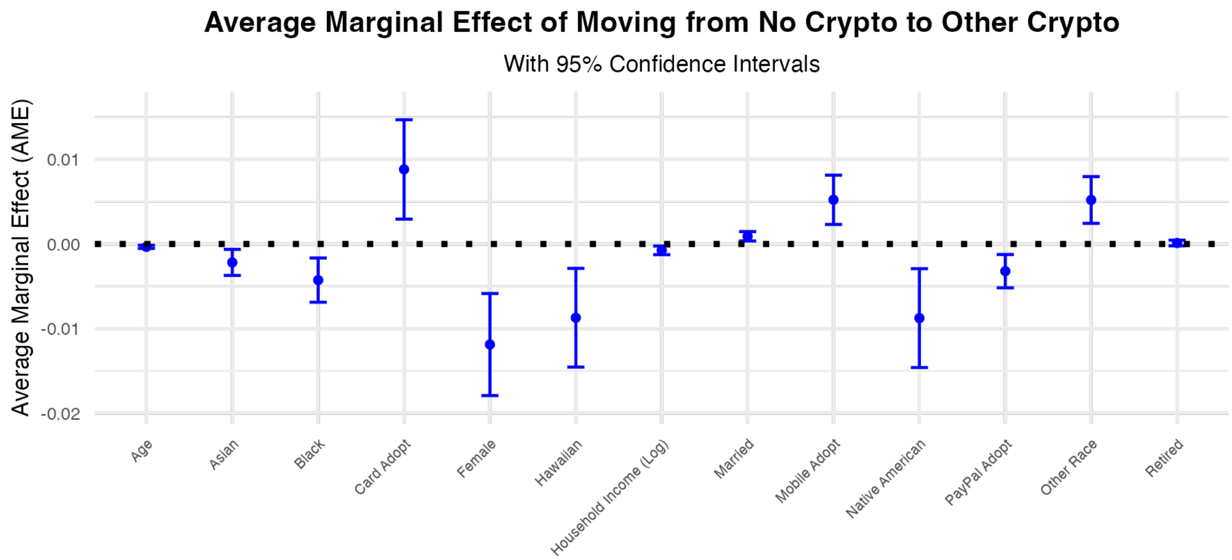

Figure 23: AME of Other Crypto Ownership

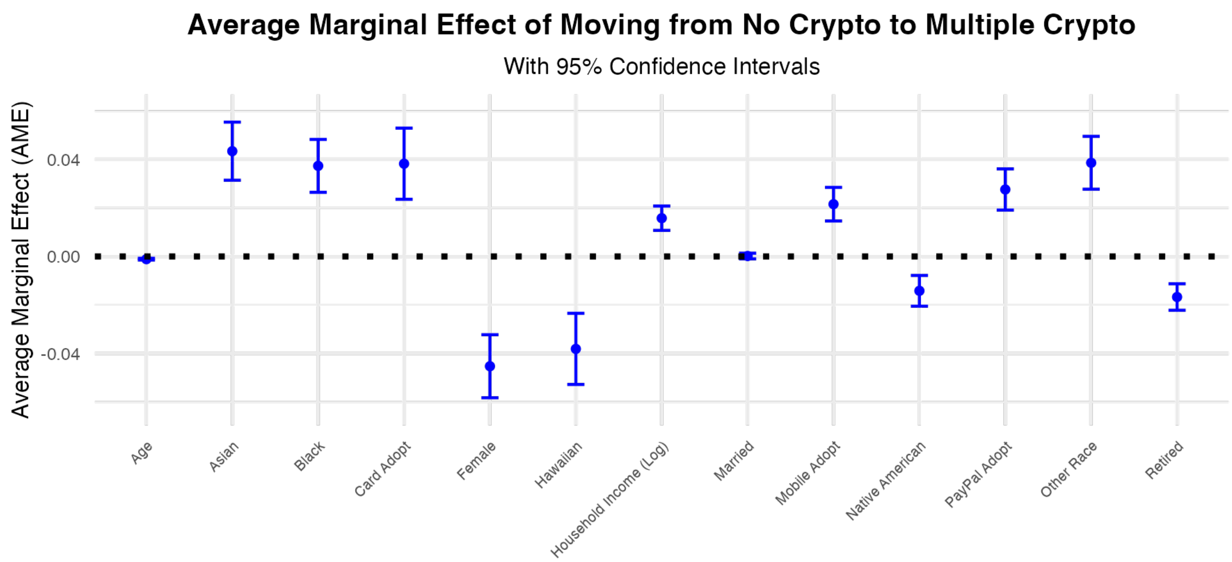

Figure 24: AME of Multiple Crypto Ownership

Crime Rates Analysis

Table 13: Crime Categorization

Crime Group	Related Crimes
Theft-Related Crimes	Robbery, Pocket-picking, Purse-snatching, Shoplifting, Theft From Building, Theft From Coin-Operated Machine or Device, Theft From Motor Vehicle, Theft of Motor Vehicle Parts/Accessories, All Other Larceny, Motor Vehicle Theft, Stolen Property Offenses, Counterfeiting/Forgery, False Pretenses/Swindle/Confidence Game, Credit Card/ATM Fraud, Embezzlement, Identity Theft, Hacking/Computer Invasion
Violent Crimes	Murder/Nonnegligent Manslaughter, Negligent Manslaughter, Justifiable Homicide, Kidnapping/Abduction, Rape, Sodomy, Sexual Assault With An Object, Fondling (Indecent Liberties/Child Molesting), Aggravated Assault, Simple Assault, Intimidation, Arson
Sexual and Human Trafficking-Related Crimes	Prostitution, Assisting or Promoting Prostitution, Purchasing Prostitution, Human Trafficking - Commercial Sex Acts, Human Trafficking - Involuntary Servitude, Incest, Statutory Rape, Pornography/Obscene Material
Gambling, Bribery, and Corruption	Betting/Wagering, Operating/Promoting/Assisting Gambling, Gambling Equipment Violations, Sports Tampering, Bribery, Money Laundering
Government/Regulatory Offenses	Weapon Law Violations, Animal Cruelty, Import Violations, Export Violations, Federal Liquor Offenses, Federal Tobacco Offenses, Wildlife Trafficking, Espionage, Harboring Escapee/Concealing from Arrest, Flight to Avoid Prosecution, Flight to Avoid Deportation, Illegal Entry into the United States, False Citizenship, Smuggling Aliens, Re-entry after Deportation, Failure to Register as a Sex Offender, Treason, Violation of National Firearm Act of 1934, Weapons of Mass Destruction, Explosives

Table 14: Crime Analysis

	(Logit)	(Probit)
Age	-0.002***	-0.002***
	(0.000)	(0.000)
Asian	0.040**	0.040**
	(0.016)	(0.018)
Black	0.022	0.025
	(0.018)	(0.018)
Card Adopt	0.918***	0.521***
	(0.059)	(0.038)
Female	-0.066***	-0.066***
	(0.010)	(0.010)
Gambling, Bribery, And Corruption	-0.045	-0.043
	(0.056)	(0.049)
Hawaiian	-0.365***	-0.291***
	(0.084)	(0.058)
Government Regulatory Offenses (Log)	0.002	0.001
	(0.019)	(0.018)
Sexual And Human Trafficking Related Crimes (Log)	-0.004	-0.003
	(0.012)	(0.011)
Theft Related Crimes (Log)	0.063***	0.065***
	(0.020)	(0.020)
Violent Crimes (Log)	-0.062***	-0.064***
	(0.022)	(0.022)
Household Income (Log)	0.012*	0.011*
	(0.007)	(0.007)
Marital Status	0.012	0.013
	(0.012)	(0.012)
Mobile Adopt	0.046***	0.045***
	(0.015)	(0.014)
Native American	-0.036	-0.040
	(0.047)	(0.043)
PayPal Adopt	0.043***	0.044***
	(0.011)	(0.011)
Other Race	0.034*	0.037**
	(0.017)	(0.018)
Retired	-0.028	-0.021
	(0.023)	(0.021)
Risky	0.012	0.013
	(0.012)	(0.012)
Highest Level of Education	✓	✓
Cash Convenience	✓	✓
Cash Security	✓	✓
Bank Account Convenience	✓	✓
Bank Account Security	✓	✓
Online Banking Convenience	✓	✓
Online Banking Security	✓	✓
Observations	4,719	4,719

Note: *p<0.1; **p<0.05; ***p<0.01