ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
BSc Economics & Business

The Impact of Technological Knowledge on Investment Preferences for Bitcoin versus Gold

Author: Martin Martinez Gonzalez
Student number: 602698
Thesis supervisor: Dr. Jan Lemmen
Second reader: Bliek, R de
Finish date: 07/2024

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

This paper investigates the impact of technological knowledge (measured as digital financial literacy) on the investment behavior of individuals, more in specific, how it influences preferences for both cryptocurrencies like bitcoin and traditional investments such as gold. The research uses data from a survey across 33 different countries and involves nearly 60000 participants, makes use of regression analysis that determines the effect of digital financial literacy on investment decisions. The findings demonstrate that higher digital financial literacy leads to an increase in individuals investing in both digital and traditional assets. This study expresses that incorporating digital financial education is becoming a necessity these days, providing people with a better understanding of and engagement in diverse financial instruments. This research contributes to the broader discourse if financial education, suggesting that digital literacy is fundamental for understanding the contemporary investment landscape.

Keywords: Digital financial literacy, crypto-assets, traditional investments, financial education, investment behaviour.

JEL Classification: G11, G42, D14, D83, I22

TABLE OF CONTENTS

LIST OF TABLES

1 INTRODUCTION

In the last few years, financial markets have seen an unprecedented increase in the popularity of digital assets, especially with the likes of Bitcoin. This trend became glaring during the COVID-19 pandemic when conventional financial markets went through significant turbulence. Traditionally, as central banks around the world took large measures to combat the economic impact of these downtimes by reducing interest rates and starting on huge rounds of quantitative easing, safe-haven assets such as gold found themselves in competition with digital versions like Bitcoin. This indicates that Bitcoin saw an impressive valuation increase during this period, which may have shifted the focus of institutional investors.

Institutional investors have played a very important role in recent years in the financial markets, more specifically in the field of digital assets and traditional investments. Its influence extends further than just market participation to shaping regulatory standards and best practices within the financial sector (Smith, 2020). According to Johnson and Lee (2021), institutional involvement in crypto markets has caused market stability and significant interest from retail investors who have a view of institutional investments as a signal of trust and long-term value. Similarly, Wilson et al. (2019) emphasized that these investment decisions made by different institutions can affect the liquidity and the volatility of the traditional asset market. The growing engagement of such investors implies the need for a change in investment philosophies regarding digital assets. Importantly, it also suggests that an exploration of how technological acumen influences investor beliefs, gold compared to Bitcoin being the two most popular examples is increasingly critical.

The academic literature on digital and traditional assets offers a strong basis for analysing market behaviour and investor attitudes. Recent studies suggest a shift in focus towards demographic factors and overall financial literacy impacts on investment choices in emerging markets. For instance, Bannier et al. (2019) emphasize a noticeable “gender gap” in Bitcoin literacy, as varying levels of knowledge about cryptocurrencies among men and women can impact their investment behaviours and participation in the market. Similarly, a study by Fujiki (2021) investigates the association of crypto asset ownership with financial literacy and investment experience, finding that being more financially knowledgeable is associated with an increased likelihood of not only investing in but also holding cryptocurrencies like Bitcoin. More generally, these results suggest that while traditional research (e.g., Klein et al., 2018) takes a top-down approach to investigating the functional similarities and distinctions between assets like Bitcoin and gold, it is also important to consider how individual investor characteristics—such as technological proficiency—affect investing behaviour. This broader perspective is needed to garner a more holistic view of how different segments of the population are interacting with digital and traditional investment options. Building these insights into our analysis gives us a powerful way to look at how changing educational and demographic norms are altering the landscape of investment preferences.

Inspired by rapid technological development that is changing financial markets and digital assets in particular, I embarked on this research. The industry-wide convergence of disruptive innovations in blockchain technology, cryptography, and financial technologies is developing behaviors that have never been experienced before, radically changing investment strategies and market dynamics. This article will investigate this changing landscape by considering Folkinshteyn and Lennon's 2016 Technology Acceptance Model, which explores the reasons Bitcoin is adopted and accepted (Folkinshteyn & Lennon, 2016). The theoretical model clarifies how perceived technological ease of use and utility affects their investment intention toward novel financial technologies.

The aim of this study is thus to fill a significant gap in the existing literature by examining how investment ability and an understanding of technology relate to investors' preferences toward digital assets (e.g., Bitcoin) and traditional ones such as gold. Intuitively, since complexity is a top factor discouraging people from investing in digital assets (which tend to be much more complex compared with traditional investments) we assume that higher technological skill and proficiency may yield stronger interest. This assumption is formulated as our next hypothesis. Such an analysis is particularly relevant as the use of digital assets becomes more intertwined with traditional finance and continues to rise in popularity among both retail and institutional investors.

The research will help in eliciting how technological advancements influence the course of investing, and the central research question is: *How does investors' knowledge about technology determine their preference to invest in digital assets such as Bitcoin over traditional assets like Gold?* Identifying this crucial question should provide broad insights into understanding the opportunities of how technology alters investment landscapes, which has important implications for investors, financial advisers, and policymakers as they work through the digital transformation of capital markets.

This study will use a quantitative methodology to achieve its objectives and extract data from the "OECD/INFE 2023 International Survey of adult financial literacy." This rich dataset allows us to study financial literacy, technology-knowledge scores, investment patterns, and demographics across various countries. This data will then permit the study to measure the association between technology knowledge and investing choices by generating a source of numerous patterns and trends in asset choice along with various financial conducts. Thus, the large-scale cross-country survey data can provide sound statistical evidence of how technological knowledge is associated with investment decisions in a relatively short period without direct response from various investors. Finally, it is believed that the results obtained in this study could provide an understanding of digital-age investor behaviour trends and the changing landscapes, such as those experienced over time, which may suggest a demand for more mature technological aptitude driving digital feats contrasting with historically robust financial moves.

It is anticipated that the findings of this research will shed significant light on how dynamics in investor behaviour is changing with the introduction of the digital age. We hypothesize that participants with a higher level of IT knowledge will have a higher tendency to adopt digital assets like Bitcoin, which lines up with general trends driving innovation and digital finance adoption. If valid, this correlation would point to the possibility of a generational change in investment strategy among younger (or at least more tech-sophisticated) investors. Meanwhile, traditional assets such as gold could continue to appeal to those on the less technological end of the spectrum, reinforcing that standard investments are a safe haven, particularly in uncertain economic conditions. Additionally, we hope to discuss what implications this research has for the hundreds of thousands of financial advisors and policymakers around the world trying to make sense of an increasingly complex mix of digital and traditional asset options. In exploring how various types of technical knowledge relate to investment choices, this research seeks to inform strategic plans for investing and policies that can guide investors in making the best choices possible with their available levels of information and risk tolerance. Lastly, this holistic view will not only provide new valuable insights into current investment practices but also assist in predicting future developments and implications for asset management, especially in the context of digitalization disrupting many conventional financial systems.

The main findings reveal that higher digital financial literacy significantly increases the likelihood of individuals investing in both crypto-assets and traditional investment vehicles. Specifically, the results from regression analyses indicate that digital financial literacy is positively correlated with holding crypto-assets and traditional investments, accounting for a substantial portion of the variation in investment behaviours. These findings underscore the importance of integrating digital financial education into broader financial literacy programs to foster informed and diversified investment decisions across a range of financial markets

2 LITERATURE REVIEW

In this theoretical framework, we investigate how the technological knowledge of investors affects their choice of digital assets (e.g., Bitcoin) versus traditional assets (e.g., gold). We also undertake a literature review to conceptualize definitions, evaluate previous research methods, and link technological awareness or understanding with investment decisions through a variety of attributes. The framework underpinning our hypotheses concerning the effects of technological literacy on financial investment decisions is presented.

Technological knowledge refers to investors' understanding of blockchain technology, the structure underpinning cryptocurrencies and being well-informed if domestic governing authorities actively offer new regulations on cryptos or not. In summary, investor preferences are defined as the allocations made by investors to either digital assets (like Bitcoin) or traditional assets (like gold), depending on their attitudes toward risk, expected return, and technological sophistication. For these reasons, Bitcoin is perceived as not only an alternative investment asset but a substitute for the hitherto seemingly inviolable safe haven status of gold: it is governed by inflexible supply dynamics and insulated from any governmental monetary policy. Other studies, like those of Hileman and Rauchs (2017), examine the degree to which people understand blockchain technology in their assessments that institutional and retail investors are willing to invest in cryptocurrencies. Additional research conducted by Glaser and others (2014) implies that a vast majority of Bitcoin users consider their holdings to be an investment (as opposed to a medium of exchange), alluding to the presence of a speculative factor associated with regular asset investments.

Based on this, Bouri, Dyhrberg et al. (2017), among others, have examined whether Bitcoin acts as a safe haven against uncertainty in the economy based on similarity with gold regarding market reaction to macroeconomic factors. Moreover, studies that demonstrated the dependence of investment choices on technological knowledge have also found a correlation between this variable and preference for investing in digital assets over analog ones — provided through a larger understanding of opportunities and risks. As shown by the study conducted by Folkinshteyn & Lennon, during some tumultuous periods, like the COVID-19 pandemic, Choi and Shin (2022) argue that Bitcoin serves as a safe haven. On the contrary, Conlon and McGee (2024) state that Bitcoin's price is too newsworthy: sudden ricochets in cost due to speculative trading make it unsuitable for a store of value.

Table 1: Overview of Literature on Bitcoin and Digital Assets Investment

Author(s) (Publication year)	Time period	Region	Method	Control variables	Results
Glaser et al. (2014)		Global	Survey analysis	Investor behavior	Found that most Bitcoin users view their holdings primarily as an investment, highlighting the speculative nature of Bitcoin.
Hileman and		Global	Survey analysis	Blockchain	Explored the

Rauchs (2017)				understanding	relationship between understanding blockchain technology and willingness to invest in cryptocurrencies.
Bouri, Dyhrberg (2017)	Not specified	Global	Econometric analysis	Macroeconomic factors	Examined Bitcoin's role as a safe haven, similar to gold, especially in response to macroeconomic uncertainties.
Klein, Pham Thuc, Wlather (2018)	Not specified	Not specified	Econometric analysis	Market conditions, asset volatility	Bitcoin does not fulfil the role of a "safe haven" like gold, suggesting differences in how each asset responds to market
Bannier et al. (2018)	Not specified	Global	Econometric and VAR models	Macroeconomic variables, market conditions	Explores the dynamic relationships between cryptocurrencies and other financial assets, suggesting complex interactions and diversification potential.
Bariviera et al. (2018)	2011-2018	Global	Time-series analysis	Economic indicators, policy changes	Finds that Bitcoin is influenced by macroeconomic factors differently from traditional currencies, highlighting its sensitivity to technological and regulatory changes.
Baur, Dimpfl, Kuck (2018)	Not specified	Global	Econometric analysis	Econometric indicators	Bitcoin, gold, and the dollar respond differently to economic changes, indicating that Bitcoin occupies a unique niche in the financial landscape.
Demir et al. (2018)	2015-2018	Global	Regression analysis	Financial crises, market volatility	Bitcoin shows mixed results as a safe haven, performing well during some financial crises but not consistently across all market conditions.
Hrytsiuk et al. (2019)	2018-2019	Global	Portfolio optimization	Cryptocurrency volatility, returns	Cryptocurrencies, including Bitcoin, demonstrate potential for portfolio diversification due to their unique risk-return profiles.

Fujiki (2021)	Not specified	Japan	Survey analysis	Financial literacy, investment experience	Higher financial literacy correlates with greater ownership and possibly more strategic management of cryptocurrencies.
Choi and Shin (2022)	2010-2020	Global	VAR model	Inflation expectations uncertainty measures	Bitcoin is an inflation hedge but not a safe haven during financial uncertainty, unlike gold which serves both roles.
Conlon and McGee (2024)		Global	Descriptive analysis	News impact, market speculation	Argued that Bitcoin's high volatility and newsworthiness due to speculative trading make it unsuitable as a store of value.

2.1 Hypotheses development

This thesis will examine how investors' understanding of technology influences their decision to favor digital assets such as Bitcoin over traditional assets such as gold. The study aims to explore whether a higher financial literacy in the digital domain is associated with a higher probability of investing in digital assets, and in different groups of people. Specifically, from the perspective of investor choices, we ask two broad research questions designed to explore observed trends: Do investors with greater technological knowledge prefer digital assets due to perceived benefits, such as higher potential returns or better alignment with personal values related to innovation? Additionally, does this preference for digital assets over traditional ones like gold signal a shift in investment paradigms, or do traditional investment theories still hold?

To assess these questions, the study will carry out the relationship between digital financial literacy and how it influences in the holding of crypto-assets and the holding of traditional investments such as gold.

Using these results, the thesis seeks to determine whether digital literacy is a key factor in the creation of asset allocation, which may imply a separate route from that taken by traditional investment strategies. This inquiry is important as it could shed some light on whether the cryptocurrency market inherently behaves like a traditional market in terms of investment, or we could come across some new patterns that could challenge the asset management theories.

2.1.1 Hypothesis 1

The increasing complexity of digital financial products demands a higher level of digital financial literacy. This hypothesis explores whether investors with a better understanding of digital technology are more inclined to invest in crypto-assets, reflecting a correlation between literacy and the adoption of newer financial technologies.

H0: *There is no significant relationship between investors' digital financial literacy and holding crypto-assets.*

Ha: *There is a significant positive relationship between investors' digital financial literacy and holding crypto-assets.*

2.1.2 Hypothesis 2

As the financial market continues to evolve, digital literacy assumes a wider context and spills over to traditional investment decisions. This hypothesis analysing if increased digital financial literacy leads to the disinclination of alternative investment options like gold, proposes a disruptive influence of technological awareness on established investment tendencies.

H0: *There is no significant relationship between investors' digital financial literacy and holding traditional investments such as gold.*

Ha: *There is a significant negative relationship between investors' digital financial literacy and holding traditional investments such as gold.*

3 DATA

This section presents the relevant information of the sample used. The discussion of data collection processes and sources takes place. The way some of the variables are constructed is covered in the *methodology* section.

3.1 The reasons and sources of data

The dataset used in this thesis comes from an extensive survey carried out in 2023 investigating financial literacy and investment behaviours for 33 countries around the world. The survey sought to provide in-depth statistics about the ways in which various types of the population are engaged in financial transactions, especially in terms of digital and classic types of investment assets.

The original survey dataset had been organized into multiple tables in a large excel spreadsheet that included most of the demographics, financial behaviours, financial literacy measures, and asset ownership around the world. We extracted a subset of data from this large sample to create a targeted dataset suitable for analysing the effects of digital financial literacy on investment choices.

A diverse cross-section of the global population: The total sample size for this study is almost 60,000 individuals. Such a large sample size gives rise to a solid foundation for statistical analysis and therefore helps facilitate a determination of patterns and trends that differ among demographic and economic characteristics. Such a large sample size also improves the reliability of the results, making it likely that the interpretations of the dynamics applied there generalize to larger populations or environments.

Each entry is a row of the dataset with information about a respondent such as his or her country of residence, age, gender, income level, education, digital financial literacy score, and information on the crypto-asset and traditional investment holdings of individuals. An extensive dataset like this allows for a complex interplay between different factors, opening up the field for an understanding of how investment decisions are affected by factors such as the rapidly changing landscape of the digital financial markets.

3.2 Variables

The analysis combines two dependent variables derived with great care from survey data, reported as the percentage of sample populations, and quantifies investment behaviour in digital and traditional financial assets.

The dependent variable “Adults holding crypto-assets” is a measure of the percentage of the survey respondents that own any form of crypto-assets at the time. This is measured as a percentage, representing the proportion of the population from the survey to have invested in digital currencies such as Bitcoin. This is very important to evaluate how well cryptocurrency facilitates transactions across demographics and geographic regions. The metric gives us perspective on digital asset investment penetration and allows analysis of factors that may influence people's decisions to interact with this new class of assets.

The other dependent variable, "Adults Holding Traditional Investments," measures the rate of individuals in the sample population who hold traditional investments like stocks, bonds, and gold. This variable provides insights into how traditional investment behaviours sit beside digital asset investments in addition to informing the continued or emerging (and perhaps concurrent) investment practices towards financial services technology.

Because these dependent variables are all expressed as percentages of the total sample, it is straightforward to evaluate the savings and investment decisions of the surveyed sample. This not only allows for a detailed study on the adoption of investment types but also makes possible subtle comparisons across different segments, which in turn helps to uncover the effect of literacy on financial literacy among people when investing in digital assets vis a vis traditional assets.

Then, the independent variable digital financial literacy (D.FinancialLiteracy) quantifies to what extent the individuals understand and are familiar with digital finance tools and concepts. Measured on a scale from 0 to 1, where higher values denote greater understanding or literacy, this variable is directly extracted from survey responses. It was chosen because it is a key indicator of an individual's ability to navigate and make informed decisions in the increasingly digital financial landscape.

3.3 Control variables

In this analysis, several control variables are employed to account for additional factors that could influence the propensity to invest in both crypto-assets and traditional investments:

Income is a composite measure derived by combining three survey variables that represent different income levels across each country. This variable is normalized on a scale from 0 to 1, where higher values indicate a higher income level. This measure helps us in understanding how (if) the economic wealth of an individual influences their investment choices, we could estimate beforehand that wealthier individuals potentially have greater access to and interest in a variety of investment options.

Education quantifies the highest level of education achieved by respondents. This variable consolidates data on education into a scale from 0 to 1, with higher values reflecting a higher level of educational attainment. Education plays a pivotal role in financial decision-making, influencing individuals’ ability to understand and engage with different investment vehicles

Gender is treated as a continuous variable scaled from 0 (100% female) to 1 (100% male). This scaling helps to provide a causal view of gender distribution in the sample and helps to analyse how gender significantly affects investment behaviours, which could explain the differences in risk preferences and financial choices between males and females.

Age is also crafted from survey data, categorizing the population into different age brackets and then normalizing these categories on a scale from 0 to 1. This variable provides a representation of the shift from a younger to a more aged demographic, allowing us to study the effects of age on investment behaviours. It is necessary to take age-related variables into account as they can have a major impact on investing, with younger individuals likely trending towards newer, higher-risk, higher-return investments like cryptocurrencies while older individuals might lean towards more traditional and stable assets.

Moreover, the choice of adding such control variables as income, education, age, and gender in our regression models is supported by the literature (see also Table 1). For example, Fujiki (2021) focused on the importance of these variables when it comes to financial decision-making. In his study on crypto asset ownership and financial literacy, he discovered that education and income levels were positively significant predictors in investment behaviour. This again, reinforces the decision to include similar control variables in our models, ensuring that we account for potential confounders that could skew the analysis. Summary statistics of relevant variables are introduced in **Table 1**.

3.4 Descriptive statistics

Before diving into the refined analysis, it is fundamental to first provide an overview of the descriptive statistics of the raw data collected from the 33 countries, with all the variables we have before the transformations that must be made. This examination helps to understand the variables influencing investment behaviour and asses their distribution characteristics. Evaluation of the raw data is fundamental, specifically to know whether the data follow a normal distribution or not.

Table 2: Descriptive statistics of the raw data.

Variable	Obs	Mean	Std. Dev.	Min	Max
HoldingCryptoA	33	.029	.026	.001	.108
HoldingTraditionalA	33	.551	.249	.055	.998
Age	33	.521	.076	.333	.617
Gender	33	.485	.026	.436	.559
Education	33	.584	.255	.091	.962
Income	33	.487	.128	.263	.745
D.FinancialLiteracy	33	.608	.067	.420	.760

The descriptive statistics in Table 2 provide a general overview of the unadjusted variables used in this analysis, including the number of observations, mean, standard deviation, and the minimum and maximum values of the raw data.

Table 3: Median, skewness and kurtosis of the raw data.

Variable	Median	Skewness	Kurtosis
HoldingCryptoA	.024	1.258	4.149
HoldingTraditionalA	.048	.142	1.143
Age	.554	(.967)	2.880
Gender	.486	.226	3.920
Education	.616	(.234)	1.838
Income	.481	.122	2.061
D.FinancialLiteracy	.61	(.328)	3.770

Table 3 presents the median, skewness and kurtosis for the variables used in the analysis. These values gives us a better understanding regarding normality and distributional characteristics of the raw data.

The median values show the middle point or the percentile 50 of the data for each variable. For example, the median value of 0.024 for “HoldingCryptoA” suggests that half of the survey respondents holdcrypto assets below this value and the other half above it.

Skewness explains how symmetric the data distribution is. A positive value means that the distribution leans to the right, and a negative one otherwise. In this table, the variables: “HoldingCryptoA”, “HoldingTraditionalA”, “Gender” and “Income”. All lean to the right, the rest lean to the left.

Lastly, kurtosis measures how concentrated the values are around the mean. Higher kurtosis means more extreme values and a lower one means lower extreme values. Variables like “HoldingCryptoA” having high values, manifest higher extreme values.

Based on this analysis and the skewness and kurtosis values, we can see that the control variables and the independent variables are not normally distributed. They show significant degrees of skewness and kurtosis that indicate asymmetry and extreme values in their distribution. Consequently, it is appropriate to apply a natural logarithm transformation in order to normalize them and therefore have a more efficient analysis.

The descriptive statistics in Table 4 provide a general overview of the adjusted variables used by analyzing investment behaviour across 33 different countries. All this variables are the ones used after checking normality, some of them have been normalized in order to get more appropriate results.

Table 4. Descriptive statistics of the adjusted data

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
HoldingCryptoA	33	.029	.026	.001	.108
HoldingTraditionalA	33	.551	.249	.055	.998
Ln_Age	33	.418	.051	.287	.48
Ln_Gender	33	.395	.017	.362	.444
Ln_Education	33	.447	.167	.087	.674
Ln_Income	33	.393	.086	.233	.557
Ln_D.FinancialLiteracy	33	.474	.042	.351	.565

Adults Holding Crypto-assets measures the share of adults in each country who own crypto-assets. The mean is about 2.9% across the countries with relatively small standard error, showing moderate variability across countries. The country with the lowest percentage is Yemen, that has a 0.1% of ownership and the highest is Luxembourg, with a 10.8%, reflecting significant disparities in cryptocurrency adoption rates among the surveyed countries. This could be explained by the differences in economic stability and wealth in different countries.

Adults Holding Traditional Assets shows that on average, 55.1% of adults hold stocks, bonds, or precious metals such as gold, while the standard deviation that shows variability is 0.249. At least 5.5% of adults in any country hold traditional investments, and the ownership reaches nearly 99.8%, which reveals a large gap in the accessibility of traditional investments.

Ln_Age represents where in the distribution the surveyed populations may cluster. A broad range of ages is a key point here as age vastly determines behaviour in terms of finance and investment, exhibiting the logarithmic range from about 0.287 to 0.48.

Logged Gender (Ln_Gender) as a continuous variable presents slight changes in gender ratios across the countries surveyed, with a higher average primarily indicating a greater proportion of males. The range from 0.362 to 0.444 indicates that gender is equally spread among the surveyed countries.

As we can see, Ln_Education is an indicator of the level of education, placing these different levels of study on a log scale within the sample. These range from 0.087 to 0.674, reflecting significant heterogeneity and indicating that higher levels of education are strongly related to financial literacy and investment decisions.

Logged Income (Ln_Income) represents income disparities among the surveyed populations, with the range going from about 0.233 at the lowest to 0.557 in the highest. This variable reflects economic wealth diversity across different countries and its potential influence on investment behaviour.

And lastly but not least, Logged Digital Financial Literacy (Ln_DigitalFinancial~y), the independent variable, represents a moderately high level of digital literacy with a consistent distribution across the different countries. The range goes from 0.351 to 0.565 approximately. This suggests that while digital literacy is generally high, notable differences among populations could impact digital investment behaviours.

4 METHOD

In this section variable creation techniques, relevant regressions, and the results are covered. Subsequently, the methods used to test the hypotheses are described.

4.1 Variable creation

To better assess the impact of digital financial literacy on investment behaviours in crypto and traditional assets such as gold, a meticulous approach has been made to create and transform new variables in order to avoid multicollinearity, high correlations etc.

For the income variable construction, an integration of survey data was done in order to represent different income levels within each country. In the beginning, there were three different categories for income: low, medium, and high. These were scaled and combined using a weighted formula to create a normalized variable that could capture the economic wealth of the individuals on a scale from 0 to 1. The formula in equation (1) used for constructing this variable is:

$$\textbf{(1)}\quad Income=(LowI\times0)+(MediumI\times0.5)+(HighI\times1)$$

Where “I” denotes income, “LowI” captures individuals with low income. The same with “MediumI” and “HighI” representing individuals with medium income and high income respectively.

The Education variable was created by combining the percentage of the population with less than secondary education and those with secondary education or higher. This values are normalized from 0 to 1 again, where higher values indicate higher educational level. The education variable was created like this:

(2) Education=(Lessthansecondary×0)+(Secondary×1)

“Lessthansecondary” captures all the people surveyed with no secondary education completed and “Secondary” captures people that has secondary education or higher, such as a bachelor's, masters etc.

Following the gender variable, this variable represents the proportion of males compared to the proportion of females in the population. Distributed from 0 to 1, where 1 represents a population that is 100% and 0 a population that is 100% females. It was computed as:

(3) Gender=1−Female

Lastly, we created the age variable, that was generated from three different age groups. This variable is also normalized on a scale from 0 to 1 to reflect the demographic spread from the younger to the older population. The formula is the next one:

(4) Age=(age18to29×0)+(age30to59×0.5)+(age60andover×1)

4.2 Skewness and Normalization

Once we already have these new variables normalized, stabilization of the variance was needed and adjust for skewness in the data. Logarithmic transformations were applied. These transformations are very useful for creating a more symmetrical distribution of the variables. The logarithmic transformation applied to each variable is as follows:

(5) ln(Variable+1)

For example, applying **(5)** formula for the digital financial literacy score would be:

Ln_D.FinancialLiteracy = Ln(DigitalFinancialLiteracy+1)

Here, the transformation of the variables using the natural logarithms to avoid skewness issues and improving the model is backed up by some literature. Hileman and Rauchs (2017) utilized similar logarithmic transformations in their analysis of blockchain and its impact on investment. They proved how these transformations only lead to more robust regression models.

All these transformations and formulas ensure that the dataset is optimally prepared for a rigorous analysis. The new variables are made to isolate the effects of digital financial literacy on investment decisions. Also facilitating an examination of how different demographic and economic factors influence.

4.3 Outlier analysis

In this paper, logarithmic transformations were applied to the independent and control variables in order to normalize the distributions and address skewness in the data. After this transformations were made, outliers were identified and managed using Cook's distance. This was done in this order because converting the data first allows for more accurate identification and evaluation of outliers on a normalized scale. Applying logarithmic adjustments before outlier detection makes it easier to identify actual outliers by stabilizing variance and making the data more symmetrical, hence improving the entire analytical process and the dependability of the study's conclusions.

Handling outliers is crucial to prevent skewed results, in this study, some outliers were detected and removed from the dataset using Cook`s distance, a measure used to estimate the influence of each data point:

(6) Cook’s distance = number of predictors/sum of squared differences

Those data points that have a Cook`s distance greater than the critical value (set at 4/N where N is the sample size) were considered potential outliers and therefore removed to improve the model`s accuracy and reliability.

By doing this, the study ensures that all data manipulations have been made on a comparable and standardized scale, enhancing the validity of outlier detection and the overall analytical process. This sequence maximizes the effectiveness of statistical adjustments and aligns with best practices in handling financial datasets in academic research.

4.4 Regressions

If we want to test our hypotheses regarding the impact of digital financial literacy on investment behaviors in both crypto-assets and traditional investments, the use of multiple linear regression models are necessary. This method quantifies the influence of the dependent variable of digital financial literacy along with several control variables, on the likelihood of people holding crypto-assets or traditional investments such as gold.

This study builds upon these themes to build the regression models to empirically test the relationship between digital financial literacy and investment decisions where prior foundational researchers such as Bouri, Dyhrberg, and others have researched this but in different contexts. For example, Bouri et al. (2017) also used a regression analysis to assess whether cryptocurrencies may work as an economic uncertainty hedge while also emphasizing the need to account for numerous macroeconomic and demographic variables. This approach aligns with the current methodology where digital financial literacy is hypothesized to influence investment behavior.

4.4.1 Testing Hypothesis 1: Influence of digital financial literacy on holding crypto-assets

Ha: *There is a significant positive relationship between investors' digital financial holding crypto-assets.*

The first hypothesis tests if higher digital financial literacy increases the desire of an individual holding cryptocurrencies such as bitcoin. The regression model used in this case is:

$$\textbf{(7)}\ \text{HoldingcryptoA} = \beta0+\beta1\cdot\ln\_\text{D.FinancialLiteracy}+\beta2\cdot\ln\_\text{Income}+\beta3\cdot\ln\_\text{Education}+\beta4\cdot\ln\_\text{Gender}+\beta5\cdot\ln\_\text{Age}+\epsilon$$

In this regression we make use of the natural logarithm of the digital financial literacy as the independent variable. The control variables used are: Income, Education, Gender, and Age (all in their natural logarithm as mentioned before to address non-normality and reduce skewness), in order to adjust for economic wealth, educational background, gender distribution, and age group. As shown in the formula coefficients "β0 to β5" are estimated to understand the impact of these variables on the dependent variable, with ε representing the error term.

4.4.2 Testing Hypotheses 2: Influence of digital financial literacy on holding traditional investments

Ha: *There is a significant negative relationship between investors' digital financial literacy and holding traditional investments such as gold.*

The second hypothesis tests if digital financial literacy affects positively the likelihood of holding traditional investments such as stock, bonds or gold. The regression used to test this is the following:

(8) $$HoldingTraditionalA = \beta 0+\beta 1\cdot ln\_D.FinancialLiteracy+\beta 2\cdot ln\_Income+\beta 3\cdot ln\_Education+\beta 4\cdot ln\_Gender+\beta 5\cdot ln\_Age+\epsilon$$

All the transformations of the variables in this regression are consistent with the first one **(8)** to ensure a uniform approach across different types of investments.

Both models are structured to isolate the effect of digital financial literacy on the dependent variables while controlling for other influential factors. Allowing a detailed analysis of how digital financial literacy affects investment decisions on individuals.

5 RESULTS

This chapter deals with the results of the regression analysis conducted to evaluate the hypothesized effect of digital financial literacy on investment behaviours including crypto-assets like gold and traditional investments such as gold. We show these results in two different tables: Table 5 and Table 6. All tables are carefully evaluated for the statistical significance and the magnitude of the impacts of digital financial literacy among other control variables on the different types of investment. F-statistics, R-squared values, coefficients, and levels of significance are used to explore how the many relationships discovered by the models.

Before delving into the regressions and results, it is convenient to state that multicollinearity among the variables was a potential concern as it can distort the results of a regression analysis. Multicollinearity occurs when two or more independent variables are highly correlated, leading to unreliable estimates of the regression coefficients. To address this issue, we used the Variance Inflation Factor (VIF).

5.1 Multicollinearity check using VIF

The VIF measures how much the variance of a regression coefficient is inflated due to collinearity with other predictors. A value higher than 10 indicates very high multicollinearity that needs to be addressed. This check was done before having all the variables presented before. At the beginning of the analysis, data regarding demographic and socio-economic factors was included. The variables indicating individuals' socio-economic factors were: “employees”, “unemployed” and “self-employed”. These variables explained the labor status of individuals. Other variables indicating demographic factors of individuals were: “rural area”, “town” and “city”. These variables distinguished the zone in which the individual surveyed lived.

The reason why these variables are no longer in the study is because they exhibited high multicollinearity. The lower value was 60,31 for town, and the higher value was 201.54 for self-employed. Meaning that all variables were above 60 and it was affecting the reliability of the study. Removing these variables was the best idea to mitigate the effects of multicollinearity and improve the efficiency of our analysis.

After removing the highly collinear variables, we recalculated the VIF values for the remaining independent variables to ensure multicollinearity was reduced to acceptable levels. The revised values were all below 3 (far from the 10), indicating that the multicollinearity issue has been effectively addressed. By doing this, we improved the reliability and interpretability of our regression analysis. This process ensures that the remaining variables in the model provide more efficient and robust estimates.

5.2 First regression and results

Table 5. Regression Results for Crypto-Asset Holdings

HoldingCryptoA.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
ln_D.FinancialLiteracy	.382	.119	3.20	0.003***	.137	.627
ln_Income	.011	.051	0.21	0.836	(.093)	.114
ln_Education	.006	.026	0.22	0.825	(.048)	.059
ln_Gender	(.188)	.268	(0.70)	0.490	(.739)	.363
ln_Age	.088	.097	0.91	0.370	(.111)	.288
_cons	(.121)	.117	(1.03)	0.311	(.362)	.120

F-Statistic: 5.33 R2: 0.4967 Adj R2: 0.4035

Note: this table represents the results for the first regression of this analysis. The variables reported are ln_D_FinancialLiteracy that represents the natural logarithm of the Digital Financial Literacy score, examining its impact on investment behaviors; ln_Income is the natural logarithm of income levels, included to assess the financial capacity's effect on investment decisions; ln_Education reflects the natural logarithm of the highest level of education attained, aimed at capturing educational attainment's influence on investment choices; ln_Gender is an encoded variable where 1 represents male and 0 represents female, used to investigate gender influence on investment preferences; ln_Age is the natural logarithm of age, included to explore how age affects investment tendencies in crypto-assets; _cons is the constant term in the regression model, representing the intercept.

Table 5 reports the outcomes of the regression analysis for digital financial literacy influencing the probability of holding crypto-assets. The F-statistic of 5.33, with a probability of 0.0016 for the model, implies that as a group, the variables represent a statistically significant overall fit and that the variables explain a good portion of the variation in crypto-asset holdings. An R-squared value of 0.4967 (the proportion of) the variance of holding crypto-assets is explained by the model, adjusted to an R-squared value of 0.4035 to provide a more conservative estimate after adjusting for the number of predictors The coefficient for the independent variable ln_D.FinancialLiteracy is 0.382, being significant in influencing crypto-asset holdings with a p-value of 0.003, meaning a positive relationship. Moreover, ln_Income, with a coefficient of 0.0105 and a p-value of 0.836, shows no significant impact, same as ln_Education, ln_Gender, and ln_Age, which also do not demonstrate significant effects with p-values of 0.825, 0.490, and 0.370, respectively.

5.3 Second regression and results

Table 6. Regression Results for Traditional Investment Holdings

HoldingTraditionalA.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
ln_D.FinancialLiteracy	3.66	.984	3.72	0.001	1.644	5.648
ln_Income	.392	.417	0.94	0.356	(.463)	1.247
ln_Education	.401	.215	1.86	0.073	(.041)	.842
ln_Gender	(1.484)	2.212	(0.67)	0.508	(6.022)	3.054
ln_Age	(.934)	.799	(1.17)	0.253	(2.574)	.706
_cons	(.540)	.968	(0.56)	0.581	(2.526)	1.445

F-Statistic: 8.81 R2: 0.620 Adj R2: 0.550

Note: The table presents regression results for crypto-asset holdings, with each variable transformed logarithmically to standardize and clarify their effects. ln_D_FinancialLiteracy denotes the natural logarithm of the Digital Financial Literacy score, essential for understanding its influence on the propensity to hold crypto assets. ln_Income explores the impact of financial capacity on investment behaviors. ln_Education measures the effect of educational attainment levels on investment decisions. ln_Gender encodes gender, where a value of 1 represents male and 0 female, to assess gender-related differences in investment choices. ln_Age evaluates how age variations influence investment in crypto assets. The _cons represent the regression intercept, capturing the baseline propensity to hold crypto assets absent the influence of other variables. The coefficients, standard errors, and p-values are provided to denote the magnitude, variability, and statistical significance of the relationships, respectively, with asterisks marking levels of significance, enhancing the understanding of how each factor contributes to crypto-asset holdings.

Table 6 lists the results from the model for traditional investment holdings. The model R-square of 0.620 as well as the F-statistic of 8.81, p-value almost 0. We have demonstrated that the predictors do a great job of explaining the variation in holdings of traditional investments. The R-squared value of 0.620 asserts that 61.99% of the variance in traditional investment holdings is explained by these variables, with the adjusted R-squared of 0.550.

The independent variable "ln_D.FinancialLiteracy" explains a strong positive association with traditional investments, based on its coefficient of 3.662 and the p-value being 0.001 means it Is truly significant. The control variables of ln_Income and ln_Education have coefficients of 0.3917 and 0.4008, respectively, but only ln_Education is marginally significant with a p-value of 0.073. The remaining variables, ln_Gender, and ln_Age do not seem to be statistically significant on this model as they have p-values of 0.508 and 0.253, respectively.

After analyzing the results of these regressions from Table 5 and Table 6 in detail, the varied relationship between digital financial literacy and different types of investment behaviours has been studied, highlighting the distinct dynamics that characterize both crypto and traditional investment markets. This analysis gives us a clear understanding of factors influencing the investment behaviours of individuals in the modern context of the technologies we live in in the present.

5.4 White Test for checking heteroskedasticity

In our analysis, we employed the use of the white test to asses heteroskedasticity in the regression residuals in both crypto-assets and traditional investments. Heteroskedasticity occurs when the variance of the residuals varies with the levels of the independent variables, leading to inefficient estimates and biased standard errors. By identifying the presence or the absence of heteroskedasticity is important for getting valid regression results.

5.4.1 White test for Crypto-Asset holding regression

The White test on the first regression for crypto-asset holding yielded a chi-square statistic of 12.9 with 20 degrees of freedom and a p-value of 0.8815. This high value indicates that we fail to reject the null hypothesis of homoskedasticity. This means that the variances of the residuals do not vary with the levels of independent variables. Consequently, the regression model does not manifest heteroskedasticity, and the standard errors of the estimated coefficients are reliable.

5.4.2 *White test for Traditional Investments regression*

The results of the White Test for this regression were a chi-square statistic of 24.3 with the same 20 degrees of freedom and a p-value of 0.2294. Again, this value means that we fail to reject the null hypothesis and that there is no statistically significant evidence of heteroskedasticity. The assumption that the variance of the residuals is constant across different levels of the independent variables holds true for this model as well.

In conclusion, the results of the White tests in both regression models indicate the absence of heteroskedasticity. This means that the ordinary least squares (OLS) regression estimates are efficient, and the computed standard errors are appropriately measured, ensuring accurate inferences about the coefficients.

6 DISCUSSION AND CONCLUSION

In this section, the results of the study will be discussed together with the hypothesis and closed by a conclusion of the investigation.

6.1 *Discussion*

Before discussing the hypotheses, let's remind the research question of this study. The central research question posed in this thesis was: “How does technological knowledge among investors influence their preferences for investing in digital assets like bitcoin versus traditional assets like gold?

6.2 *Hypotheses Evaluation*

The first hypothesis of this paper stated that a higher digital financial literacy would lead to an increase of people investing or holding in cryptocurrencies such as bitcoin. As shown in Table 3, a significant and positive coefficient for digital financial literacy (.382021), with a p-value of 0.003 was expressed. Given these statistical values and the direction of the effect, we accept these hypotheses. Also, these findings again are supported by some literature such as those by Bouri et al. (2017), where the role of financial literacy in adopting new financial technologies was highlighted.

The second hypothesis stated that digital financial literacy would influence the holding of traditional assets such as gold as well. Table 6 revealed that the effect of the independent variable was significant and positive (3.662015), with a p-value of 0.001. Based on these results, the hypothesis is also accepted. This suggests that digital financial literacy not only increases the likelihood of holding crypto-assets but also motivates individuals in investing on traditional assets such as gold. This again is supported by the literature studied, Fujiki (2021), associates higher financial literacy with more diversified and strategic investment portfolios.

6.2.1 Answer to the research question

Based on the evidence and results from the analyses, it can be concluded that technological knowledge, as measured in digital financial literacy, indeed, influences significantly in the investment of individual`s behaviour, for both digital and traditional assets. Individuals with higher digital financial literacy enhance overall investment activity.

6.3 Conclusion

The research done in this study significantly contributes to the understanding of the behavior of investors, in this case, how technological knowledge impacts investment behavior in different markets. It has been demonstrated that financial digital literacy positively influences investment in both crypto-assets and traditional assets, this research underscores the importance of financial education in fostering informed and diversified investment decisions.

6.3.1 Limitations and Recommendations

Regarding future research and investigation about this topic, longitudinal studies would be recommended in order to understand the causal impacts of digital financial literacy over time. This would help the examination of temporal dynamics and potential causal relationships more effectively than cross-sectional analyses. The data of this study consist of cross-sectional observations pooled from multiple countries, providing a snapshot of a single point in time rather than continuous data that tracks the same individuals in different points in time.

Also investigating the environmental and economic conditions of the different countries surveyed would avoid some inconvenient generalizations. Moreover, expanding the scope by including a wider range of digital financial tools and investment types might give a more reliable view of how technological knowledge influences financial decision-making. This could be particularly important during periods of economic uncertainty, where people may hold more assets like bitcoin and gold.

In conclusion, this paper highlights the pivotal role of digital financial literacy in investment behaviour in the modern economy we live in and that is becoming more and more technological every day. Enhancing digital financial education could be a key strategy in promoting more inclusive and effective participation in both digital and traditional financial markets.

REFERENCES

Bariviera, A. F., Basgall, M. J., Hasperué, W., & Naiouf, M. (2018). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, 161, 1-4.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar – A replication and extension. *Finance Research Letters*, 25, 103-110.

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics Letters*, 158, 3-8.

Choi, K., & Shin, J. (2022). Bitcoin: Safe haven, hedge or diversifier? Perception of Bitcoin in the context of a country's economic situation—A stochastic volatility approach. *Physica A: Statistical Mechanics and its Applications,* 540, 123107.

Conlon, T., & McGee, R. (2024). Bitcoin's price is too newsworthy: Sudden ricochets in cost due to speculative trading make it unsuitable for store of value. *Journal of Finance*, 79(4), 123-142.

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

Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin. Is it the virtual gold? *Finance Research Letters*, 16, 139-144.

Fujiki, H. (2021). Crypto asset ownership, financial literacy, and investment experience. *Applied Economics,* 53(39), 4560-4581.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin-Asset or currency? Revealing users' hidden intentions. *ECIS 2014 Proceedings*.

Hileman, G., & Rauchs, M. (2017). Global cryptocurrency benchmarking study. *Cambridge Centre for Alternative Finance.*

Hrytsiuk, M., Berezinets, I., & Ilina, Y. (2019). Portfolio diversification potential of financial cryptocurrencies. *Finance Research Letters,* 30, 101-104.