Payoff over Panorama: Mental Accounting and Asset Class Selection

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Abstract

This study examines how mental accounting shapes the participation and asset class selection decisions of individuals. Using a unique question from the Dutch National Bank Household Survey, I identify individuals with mental accounting bias.This enables me to compare the financial decisions of individuals with and without this bias to determine its impact on investment behavior. My findings show that mental accounting is associated with 3.5% lower participation in risky markets, representing a 12% relative decrease. However, conditional on investing, individuals with mental accounting bias favor high-risk, high-return assets. Specifically, compared to individuals without this bias, they are 30% more likely to invest in cryptocurrencies but 20.7% and 22.7% less likely to invest in stocks and mutual funds, respectively. Moreover, among those who invest, individuals with mental accounting bias are most likely to exclusively hold cryptocurrencies, avoiding diversified portfolios. The influence of mental accounting extends to other investments, including real estate, bonds, options, and individual stock selection, and it is persistent over time. The findings align with Mental Accounting theory and help explain risk-taking behaviors beyond what risk and loss aversion alone can account for.

Keywords: Behavioral Finance, Mental Accounting, Household Finance, Investments

JEL Codes: D14, G41, G50, G51

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Abstract

This study examines how mental accounting shapes the participation and asset class selection decisions of individuals. Using a unique question from the Dutch National Bank Household Survey, I identify individuals with mental accounting bias. This enables me to compare the financial decisions of individuals with and without this bias to determine its impact on investment behavior. My findings show that mental accounting is associated with 3.5% lower participation in risky markets, representing a 12% relative decrease. However, conditional on investing, individuals with mental accounting bias favor high-risk, high-return assets. Specifically, compared to individuals without this bias, they are 30% more likely to invest in cryptocurrencies but 20.7% and 22.7% less likely to invest in stocks and mutual funds, respectively. Moreover, among those who invest, individuals with mental accounting bias are most likely to exclusively hold cryptocurrencies, avoiding diversified portfolios. The influence of mental accounting extends to other investments, including real estate, bonds, options, and individual stock selection, and it is persistent over time. The findings align with Mental Accounting theory and help explain risk-taking behaviors beyond what risk and loss aversion alone can account for.

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1 Introduction

Households show puzzling behavior when it comes to investing. On one hand, a large body of research documents the persistent reluctance of many individuals to participate in traditional, well-diversified stock markets, despite their historically attractive risk-return profiles (Mankiw and Zeldes, 1991; Haliassos and Bertaut, 1995; Mehra and Prescott, 1985; Heaton and Lucas, 1997). On the other hand, many individuals who previously avoided conventional equity markets have actively turned to speculative investments such as cryptocurrencies, meme stocks, and options trading.[1]

A conventional explanation for these contrasting investment patterns is heterogeneity in risk tolerance. However, data from surveys such as the Survey of Consumer Finances (SCF) and the FINRA Financial Capability Study suggest that self-reported risk preferences are not highly polarized. Most individuals describe themselves as having low to moderate risk tolerance.[2] This raises an important question: What drives individuals' financial risk-taking if it is not explained solely by risk tolerance?

One possible explanation comes from the Barberis, Huang, and Thaler (2006) model, which incorporates mental accounting. Mental accounting is a behavioral bias in which individuals mentally segregate their money into different "accounts" based on subjective criteria such as the source or intended use of funds (Thaler, 1985). Via a theoretical model, Barberis, Huang, and Thaler (2006) study in detail the impact of mental accounting on investor choices. They find that mental accounting leads investors to evaluate potential investments in isolation rather than as part of a diversified portfolio. As a result, they may reject low-risk, low-return investments because the potential gains are perceived as too small to compensate for their fear of losses. Conversely, they

[1] Weber et al. (2023) find that 20% of crypto investors invest primarily in cryptocurrencies rather than stocks.

[2] FINRA 2015: A Snapshot of Investor Households in America shows a 4.8 average risk tolerance on a 10-point scale; in the 2016 SCF, 20.5%–21.8% of respondents reported high risk tolerance

may pursue high-risk, high-return investments when the potential gains seem large enough to offset their loss aversion. Because they evaluate investments in isolation and do not derive utility from diversification, these investors either focus on opportunities with outsized returns or avoid risky markets altogether.

Empirical studies show that mental accounting bias is widespread, with 25% to 53% of individuals in representative samples exhibiting this bias (Antonides, 2017). Meta-analyses confirm its presence across diverse populations worldwide (D'Ambrogio et al., 2023)[3] Kahneman and Tversky's (1984) experiments highlight the magnitude of its effect, showing that individuals can be nearly twice as willing to spend depending on which mental account the transaction falls into.

The theoretical predictions in Barberis, Huang, and Thaler (2006) align with observed market behaviors, and the prevalence and magnitude of mental accounting bias suggest that it could influence investor behavior. Still, it remains an open empirical question whether mental accounting actually drives such behavior in real-world settings. Prior research has inferred mental accounting from patterns in market data, such as clustered trades (Kumar, 2009) and capital gains overhang (Grinblatt and Han, 2005), or from variations in how financial information is presented (Choi et al., 2009). Yet these studies do not directly identify which individuals exhibit mental accounting bias. As a result, we still know little about how mental accounting affects financial decision-making at the individual level, or how the behavior of individuals with the bias differs from that of individuals without it.

The Dutch National Bank Household Survey (DHS) helps overcome this limitation by including a unique question that directly identifies individuals with mental accounting bias. This measure enables a more direct investigation into how the bias shapes real-world investment behavior.

Leveraging this data, I draw on the theoretical framework of Barberis, Huang, and Thaler

[3] My sample shows a similar prevalence rate (41%).

(2006) to test whether mental accounting can explain both non-participation in risky markets and, conditional on participation, a preference for high-risk, high-return assets such as cryptocurrencies and options over lower-risk alternatives like stocks, mutual funds, bonds, and real estate. I also disentangle the mechanisms proposed in the model to assess whether mental accounting explains variation in participation decisions beyond what can be attributed to risk aversion or loss aversion.

The Dutch National Bank Household Survey (DHS) is particularly well-suited for my study for several reasons. First, it is a nationally representative survey of the Dutch population, ensuring that my findings are not confined to specific demographic subgroups. Second, alongside the unique question on mental accounting, it also includes information on a broad range of behavioral variables such as optimism, financial literacy, risk tolerance, and loss aversion. This allows me to isolate the effect of mental accounting while also capturing related components such as risk tolerance and loss aversion, which are central to the theoretical model. Third, the DHS covers various asset classes, including cryptocurrencies, stocks, mutual funds, bonds, real estate, and options. This allows me to generalize my findings and link them to different payoff structures, ensuring that the patterns reflect broader investment behavior rather than investment in a single asset class. Finally, the survey spans multiple waves, enabling me to track investors over time and determine whether these behaviors persist or change.

Building on the mental accounting measure in the DHS, I construct a binary indicator to identify individuals who exhibit mental accounting tendencies. I apply a two-step empirical strategy to both the full sample and the subsample of market participants. In the first step, I examine whether mental accounting affects the decision to participate in risky asset markets. In the second, I analyze its influence on the selection of specific asset classes. This framework allows me to distinguish the impact of mental accounting on market entry from its role in portfolio composition.

To more rigorously address the distinction between participation and asset selection, I also estimate a Heckprobit selection model. This method corrects for potential selection bias by modeling market participation in the first stage and asset class selection in the second.

I find that individuals with mental accounting tendencies are generally less inclined to invest. However, if they do invest, they are more likely to select high-risk, high-return asset classes like cryptocurrencies and are less likely to choose lower-risk asset classes such as stocks and mutual funds. In economic terms, mental accounting is associated with a 3.5% decrease in risky market participation (a 12% relative decline) and a 1 percentage point increase in cryptocurrency participation, equivalent to a 30% relative increase. Conversely, it corresponds to a 2.3% decline in stock market participation (a 20.7% relative decrease) and a 2.7% decline in mutual fund participation (a 22.7% relative decrease). These effects remain significant even after I control for demographic characteristics, socioeconomic factors, financial knowledge, and risk tolerance, indicating that mental accounting plays a distinct role in shaping investment decisions.

Given the relatively low participation rates in the Netherlands (3.5% for cryptocurrencies, 9% for stocks, and 12% for mutual funds), the economic significance of these findings is substantial. The magnitude of the effect of mental accounting is comparable to that of other behavioral factors such as sociability (Georgarakos and Pasini, 2011), social interaction (Hong, Kubik, and Stein, 2004), and political activism (Bonaparte and Kumar, 2013).

To further examine the influence of mental accounting, I focus on three key areas. First, I address a common counterargument: some individuals may invest in cryptocurrencies to diversify their portfolios by adding high-risk assets. If this were the case, it would suggest that their investment decisions stem from a holistic strategy rather than compartmentalized decision-making. While this explanation may apply to some investors, my findings suggest it does not hold for those with mental accounting tendencies. These individuals are significantly more likely to invest exclusively in cryptocurrencies than to combine them with traditional assets, which suggests that their choices are not motivated by diversification. Instead, they tend to concentrate their portfolios in high-risk, high-return assets while avoiding lower-risk alternatives. Among individuals who participate in risky markets, I find that general risk tolerance does not significantly predict exclusive cryptocurrency investment, although it remains a significant factor for those who hold both cryptocurrencies and traditional assets. This pattern indicates that mental accounting, rather than risk tolerance alone, drives exclusive investment in cryptocurrencies.

Second, I extend the analysis to test whether mental accounting influences investment decisions across asset classes based on their statistical properties, rather than being specific to cryptocurrencies. I find that mental accounting is negatively associated with participation in lower-risk investments such as bonds and real estate (excluding primary residence) but positively associated with options, which have a high-risk, high-return profile when used speculatively, as is common among retail investors (Pavlova, 2023).

Third, to move beyond isolated participation decisions, I run an ordered logit model to examine how the association between mental accounting and the likelihood of investing in certain asset classes changes gradually as assets range from lower-risk, lower-return investments to higher-risk, higher-return ones. I find that mental accounting reduces the likelihood of investing in the safest assets, such as bonds and real estate, and has a weaker negative effect on investment in stocks and mutual funds. The relationship then turns positive for individuals who hold both cryptocurrencies and traditional assets, with the strongest positive effect for those who invest exclusively in cryptocurrencies.

Additionally, I find suggestive evidence that when investors who exclusively held cryptocurrencies exit the market, they tend to withdraw from investing entirely rather than reallocating their funds to other asset classes. These findings are consistent with the hypothesis that mental accounting contributes to an all-or-nothing investment pattern, where individuals either avoid participation altogether or concentrate their investments in high-risk, high-return assets.

After examining how mental accounting influences investment behavior, I turn to a key question: Is this bias a stable cognitive trait, or does it vary over time and across financial contexts? Understanding its stability is crucial. If mental accounting remains consistent across time and investment settings, it likely reflects a fundamental aspect of financial decision-making and should be incorporated into behavioral models. If instead its influence depends on context, its relevance may be limited to specific conditions, which would affect how we interpret its role and apply theoretical frameworks (Stigler and Becker, 1977).

To examine this, I analyze data from multiple waves of the DHS, focusing on individuals who appear in all survey waves over the sample period. I find that those who consistently exhibit mental accounting tendencies over time are more likely to invest in cryptocurrencies. In contrast, individuals who display these tendencies only intermittently do not show the same asset selection patterns. These results suggest that the observed behaviors are driven primarily by individuals with persistent mental accounting tendencies, rather than by temporary shifts in mindset or context.

Next, I extend the analysis to test whether mental accounting affects stock selection in a similar way to how it influences asset class selection. I find that individuals with mental accounting tendencies tend to choose higher-risk stocks with more extreme returns. This mirrors the patterns found in my main analysis. The results show that mental accounting influences various investment decisions and is driven by risk-return profiles, not by features unique to cryptocurrencies.

My main results are robust to using different methodologies. For instance, I use coarsened exact matching (CEM) to match individuals with and without mental accounting tendencies on key characteristics such as age group, income quintile, education, gender, financial knowledge, and risk tolerance. CEM places individuals into coarsened bins for each variable and then forms matched pairs that are as similar as possible across these dimensions. This method improves group balance and reduces potential bias from confounding factors.

I also run an instrumental variable analysis using childhood pocket money as an instrument for mental accounting. Prior research shows that early financial experiences can shape financial behavior later in life (Malmendier and Nagel, 2011, 2016; Malmendier, Tate, and Yan, 2011). Receiving pocket money teaches children to separate money based on its source or intended use. For example, they may use pocket money for small treats and rely on parental money for necessities. This habit of mentally assigning money to different categories can persist into adulthood and lead to mental accounting in financial decisions.

I run this IV analysis only on market participants to avoid confounding the effect of pocket money with the possibility that wealthier parents provided more financial resources for investment. This ensures that the relationship between mental accounting and investment decisions reflects ingrained budgeting habits, not differences in financial background or access to resources.

I also repeat the main analysis using an alternative measure of mental accounting: the number of individual checking accounts, controlling for total funds held. The consumption literature (Thaler, 1999) suggests that individuals with mental accounting tendencies are more likely to separate money by purpose using multiple accounts. I adjust for cases where accounts may serve liquidity needs or are shared with spouses or family. This alternative measure helps address concerns about measurement error in the survey question and supports its effectiveness in capturing mental accounting behavior.

My paper contributes to the extensive literature on behavioral biases in financial decision-making (Barber and Odean, 2000, 2001; Shefrin, 1985; Huberman, 2001). Mental accounting offers one explanation for why individuals often deviate from rational utility maximization. Several studies have incorporated mental accounting into traditional theoretical models to better capture real-world behavior. For example, Barberis and Huang (2001) and Barberis, Huang, and Thaler

(2006) incorporate mental accounting into their frameworks to explain phenomena such as non-participation, individual stock returns, and asset allocation, while Das et al. (2010) extend this approach by integrating mental accounting into portfolio optimization.

Building on these theoretical advancements, empirical studies have provided important insights into the market-level consequences of mental accounting (Grinblatt and Han, 2005; Frydman et al., 2018; Seiler et al., 2012). My study contributes to this literature by providing one of the first empirical analyses to directly identify individuals with mental accounting bias, test predictions from existing models, and examine the implications of this bias at the individual level. While Kouwenberg and Dimmock (2009) test elements of the Barberis et al. (2006) model, they focus on loss aversion and treat mental accounting as given. Yet Barberis et al. (2006) show that loss aversion alone cannot explain non-participation. I extend this line of research by showing that mental accounting varies across individuals and has a distinct, measurable effect on investment behavior.

Moreover, while Kouwenberg and Dimmock (2009) focus solely on explaining non-participation, I test the full structure of the Barberis et al. (2006) model, which involves non-participation in the stock market and the simultaneous acceptance of G_L (a high-payoff, high-risk gamble). While it is possible to model non-participation by assuming high levels of loss or risk aversion, such assumptions would also imply rejection of G_L. This contradiction highlights the central role of mental accounting in reconciling the two outcomes. By empirically testing both sides of the decision pattern, I provide a more complete evaluation of the theoretical framework.

I also contribute to the literature on mental separation. Choi et al. (2009) show that presenting information separately can lead investors to allocate assets without considering their other accounts. Kumar (2009) finds that clustering trades into a single mental account reduces the disposition effect and improves diversification. More recently, Gargano and Rossi (2020) demonstrate that goal-setting features in fintech apps promote saving by encouraging the mental separation of funds. I extend this line of research by showing how mental separation influences risk-taking behavior.

My research also contributes to the growing literature on cryptocurrency investor behavior. Kogan et al. (2024) find that individuals who invest in both cryptocurrencies and stocks exhibit distinct trading patterns across these asset classes, and these patterns cannot be explained by demographic differences. Aiello et al. (2023) show that investors have a significantly higher marginal propensity to consume from crypto gains than from gains from other assets. Weber et al. (2023) document that many investors allocate a substantial portion of their financial wealth to cryptocurrencies. While these patterns suggest a potential link to mental accounting, these registry-based studies do not directly measure psychological biases. My research addresses this limitation by using a survey-based approach that enables the identification and isolation of mental accounting bias in cryptocurrency investment decisions.

The rest of the paper is structured as follows: Section 2 discusses the theoretical foundation behind my analysis. Section 3 outlines the data used in the analysis. Section 4 identifies mental accounting tendencies and presents the main results. Section 5 explores the underlying mechanisms through conditional hypotheses. Section 6 addresses alternative identification strategies, and Section 7 examines the consistency of the bias. Section 8 presents the robustness checks and external validity, and Section 9 concludes the study.

2 Theoretical Framework and Hypothesis Development

The hypotheses of my empirical analysis are based on the theoretical framework developed by Barberis, Huang, and Thaler (2006), which aims to explain a paradoxical choice pattern: in a series of experiments, individuals often rejected a low-risk, low-return investment with a win/loss ratio of

\$550/\$500 (denoted as G_S) yet accepted a high-risk, high-return investment with a win/loss ratio of $\$20,000,000/\$10,000$ (denoted as G_L). This behavior contradicts standard utility models, which predict that individuals should either accept both G_S and G_L or reject both.[4]

Attempts to reconcile this discrepancy by adjusting the utility framework have struggled to fully explain these behavioral anomalies. Even allowing for first-order risk aversion is not sufficient. Loss-averse individuals should still accept G_S because it helps them to diversify pre-existing risks, such as human capital or housing risk. Rejecting G_S would therefore require implausibly high levels of risk aversion (and/or loss aversion) that would also predict rejection of G_L. Barberis, Huang, and Thaler (2006) address this by incorporating mental accounting into non-expected utility functions with first-order risk aversion (R-FORA). In this framework, individuals evaluate each investment in isolation, without considering its role in diversifying total risk. As a result, they may reject G_S while still accepting G_L. Thus, while loss aversion plays a key role, the addition of mental accounting allows the model to fully account for the rejection of G_S.

Barberis, Huang, and Thaler extend their analysis to real-world assets by using their framework to calibrate non-participation in the stock market. They use the stock market as a proxy for G_S, while showing that individuals simultaneously accept G_L. My goal is to test whether individuals with mental accounting bias follow this decision pattern in practice. Continuing to use stock market participation as a proxy for G_S is straightforward. However, finding a suitable proxy for G_L requires more careful consideration. Barberis et al. describe G_L as involving higher stakes and a favorable payoff. While no real-world asset matches the payoff of G_L exactly, I look for one that, from a statistical perspective, offers a high expected return and has higher stakes.

Among the asset classes in my data, cryptocurrencies offer the closest statistical match to G_L in terms of return characteristics. I focus this theoretical section on three widely traded and

[4]For a more detailed discussion on the limitations of traditional utility frameworks in explaining this behavior, see Barberis, Huang, and Thaler (2006).

well-established coins: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). I select these coins because they represent about 75% of all retail crypto trading (Kogan et al., 2024). This makes them representative of household investment behavior. For example, BTC delivered an average annual return of 62% between 2018 and 2022, with a standard deviation of 1.524. From a purely statistical perspective, this represents a very attractive return, paired with considerable risk.

It is important to note that the return distributions of BTC, ETH, and XRP differ from those typically associated with probability overweighting or lottery-like stocks. These theories suggest that individuals are drawn to assets with low-cost entry and extremely rare but large payoffs, due to an overweighting of small probabilities (Kahneman and Tversky, 1979; Barberis and Huang, 2008; Dimmock et al., 2018). In contrast, BTC, ETH, and XRP exhibit fat-tailed return distributions, where both large gains and large losses occur relatively often. While G_L assumes a more favorable structure—with gains much larger than losses—cryptocurrencies represent the closest real-world counterpart available in my data.

To further validate cryptocurrencies as a suitable proxy for G_L, I conduct a simulation using field parameters to assess whether the model replicates the behavior observed in the original G_S and G_L simulations by Barberis, Huang, and Thaler (2006). Specifically, I calibrate the mental accounting utility framework using the expected return and standard deviation of BTC, ETH, and XRP, based on annual price data from Yahoo Finance for the period 2018 to 2022. This time span aligns with the waves of the household survey data I later use in the empirical analysis.[5][6] I focus this section on BTC results and report the ETH and XRP simulations in the Appendix to support the generalizability of my findings.

For G_S, I use annual data from the Amsterdam Exchange Index (AEX), which reflects tradi-

[5] I also test alternative time spans and find consistent results.

[6] The household survey waves span 2019 to 2023 and include retrospective questions about cryptocurrency holdings in the previous year.

tional stock market investments with lower risk and lower expected returns. I choose the AEX to maintain consistency with the Dutch household survey data. To enhance generalizability, I also run the simulations using data from the S&P 500. These additional results appear in the Appendix.

The simulation results, presented in Figure 1, show patterns similar to those in Barberis, Huang, and Thaler (2006). Without mental accounting, there is no overlap between the regions where individuals reject stock market participation (G_S) and accept BTC as a proxy for G_L. Modeling non-participation in G_S requires unrealistically high levels of loss aversion (γ) and risk aversion (λ), which would also imply rejection of G_L. However, once I introduce mental accounting into the model, a substantial overlap appears. Individuals with mental accounting bias may simultaneously avoid stock market participation while choosing to invest in BTC.

The simulation results based on the BTC and AEX parameters closely follow the theoretical predictions in Barberis, Huang, and Thaler (2006), supporting the relevance of my empirical setting. For reference, I include the original simulation results from their study in the Appendix.

Although no real-world asset perfectly replicates the payoff structures of G_S and G_L, both the stock market and cryptocurrencies behave similarly enough in the simulations and are sufficiently accessible to households. This makes them appropriate empirical counterparts for testing the theory. To further strengthen external validity, I also include additional asset classes in my empirical analysis.

Based on the theoretical framework and simulation results, I formulate the following hypotheses for my empirical analysis:

H1: *Mental accounting helps to explain non-participation in risky markets. However, conditional on participation, individuals with mental accounting bias are more likely to favor high-risk, high-return assets like cryptocurrencies and less likely to invest in lower-risk, lower-return assets such as stocks and mutual funds.*

H2: *The effect of mental accounting is stronger among individuals who exclusively invest in cryptocurrencies than among those who hold both cryptocurrencies and traditional assets.*

H3: *Loss aversion helps to explain non-participation in traditional assets and exclusive investment in cryptocurrencies.*

3 Data

I use data from the annual Dutch National Bank Household Survey (DHS). This survey covers a wide range of information about households, including demographics, assets and liabilities, and behavioral characteristics. Its comprehensive coverage of financial matters has been extensively utilized to analyze the financial behavior of households (van Rooij, Lusardi, and Alessie, 2011; von Gaudecker, 2015; Dimmock and Kouwenberg, 2010; Korniotis and Kumar, 2011; Anantanasuwong and Pengnate, 2020).

Each year, households are randomly selected to participate in the survey, which is conducted online. To prevent selection bias, special provisions are made for those without internet access, ensuring that the sample remains representative of the Dutch population. The survey covers approximately 3,500 individuals annually. For my cross-sectional analysis, I utilize five waves of data from 2019 to 2023, focusing on these later waves because earlier ones do not include information on cryptocurrency participation. Because not all respondents complete the asset section and my analysis incorporates an extensive list of controls, my final dataset comprises 12,860 observations for which I have complete data.

I conduct my main analysis at the individual respondent level, recognizing that many cryptocurrency investors belong to the younger generation and that a significant portion of couples in the Netherlands make independent financial decisions or maintain separate bank accounts (Raaij et al., 2020). However, I also conduct analyses focusing exclusively on heads of households and apply various robustness tests to account for similar decision-making patterns within households. My main findings remain consistent across these different approaches.

Table 1 presents summary statistics for the main controls and variables of interest in this study, both for the full sample and the subsamples of interest. The sample consists of 51% males, with 38.5% having college or vocational education. The average income is €39,819, and the average age is 55. I measure high risk tolerance using an indicator variable equal to one for individuals whose average risk preference, based on their responses to several risk-related questions, is above 4 on a scale from 1 to 7. Financial literacy is assessed on a self-reported scale from 1 to 5, with 5 being the highest.[7] In my sample, 41.5% of respondents exhibit mental accounting behavior. I will elaborate on the construction of this variable in the next section. Participation rates in financial assets are 12% for mutual funds, 9% for individual stocks, and 3.5% for cryptocurrencies.

My analysis focuses on the direct ownership of individual stocks, mutual funds, and cryptocurrencies. In the Netherlands, the pension system is primarily collective and mandatory, with pension funds managed by professional institutions. This system limits individual discretion over pension investments, in contrast to the more flexible, discretionary approach common in the United States. As a result, I focus solely on direct investments, as these are the ones over which Dutch investors have full discretion.

Given my primary focus on asset class selection and mental accounting, Panels B, C, and D present the descriptive statistics for the three categories of interest in this study: cryptocurrency investors, traditional investors (those investing in stocks and mutual funds), and individuals exhibiting mental accounting bias. I classify an individual as a traditional investor if they exclusively hold stocks or mutual funds. If they hold both traditional assets and cryptocurrencies, I cate-

[7] Lusardi and van Rooij (2011) report a high correlation between self-assessed and objectively measured financial literacy in earlier waves of the same survey.

gorize them as cryptocurrency investors. The demographic and socioeconomic characteristics of cryptocurrency and traditional investors in my sample are consistent with existing literature (e.g., Lusardi and Mitchell, 2011; Aiello et al., 2023; Weber et al., 2023; Pursiainen and Toczynski, 2022; Hackethal et al., 2022). Cryptocurrency investors are younger (average age 43) than traditional investors (average age 59). Both groups tend to have higher income levels (€45,460 and €47,711, respectively) and are predominantly male, are financially literate, and have college education.

Individuals with mental accounting bias are slightly younger (average age 52), have higher incomes (€41,683), and are slightly more likely to be female (52.3%), with higher education and financial literacy levels. The demographics of the mental accounting subsample align with findings in the psychology literature (Antonides et al., 2011; Muehlbacher et al., 2017), supporting the validity of my method for identifying mental accounting bias. Importantly, these individuals do not exhibit lower financial sophistication or higher risk appetite. Their distinct demographic profile compared to both cryptocurrency and traditional investors underscores that mental accounting bias is not merely a reflection of a specific subgroup of the population.

4 Mental Accounting

4.1 Identifying Mental Accounting

One of the key components of mental accounting is that individuals break financial decisions into smaller, more manageable parts. This involves grouping these decisions and their associated outcomes into separate mental accounts, where each decision and its outcome are evaluated independently, isolated from other accounts (Thaler, 1999). Previous research has employed various methods to identify these mental accounts, including capital gains overhang (Grinblatt and Han, 2005), reinvestment days (Frydman et al., 2018), and clustered trades (Kumar and Lim, 2008)).

While these studies provide valuable insights into the potential market effects of mental accounting by leveraging exogenous separation and clustering in market settings, they do not clearly distinguish whether individuals exhibit mental accounting bias. Fortunately, the DHS survey includes a specific question that I use to identify mental accounting bias in individuals. I consider this question well-constructed because it addresses the outcomes of mental accounting without directly prompting participants to admit to biased decision-making, which they may be reluctant to acknowledge. Specifically, the survey asks: *"Do you put money aside for particular purposes (holidays, clothes, rent, etc.) in order to reserve separate amounts for different purposes? For example, by depositing money into separate bank accounts, or by putting money in separate envelopes or jars."* Based on this question, I generate a binary mental accounting indicator variable, classifying individuals who responded affirmatively as exhibiting mental accounting bias. To demonstrate that responses to this survey question translate into actual behaviors, such as maintaining multiple accounts for different purposes, I apply additional identification strategies in the robustness section.

Figure 2 illustrates how mental accounting bias relates to investment behavior by showing deviations from the full sample mean participation rate across four groups: non-participants, cryptocurrency investors, traditional asset holders, and those who hold both. The figure indicates that individuals with mental accounting bias are more likely to either hold cryptocurrencies—whether exclusively or alongside traditional assets—or not participate in financial markets at all. In contrast, they are significantly less likely than those without mental accounting bias to invest only in traditional financial assets.

4.2 Mental Accounting and Asset Class Selection

To test H1, I employ the following logistic regression model[8]:

$$\text{Participation}_i = \alpha + \beta_1 \text{MentalAccounting}_i + CX_i + \tau_t + \varepsilon_{prov,t} \tag{1}$$

where Participation_i represents one of the four participation indicators under investigation (overall participation, cryptocurrencies, stocks, or mutual funds) for individual i. The variable $\text{MentalAccounting}_i$ is the mental accounting indicator, X_i is a vector of control variables including demographic factors such as gender, education, income, and age, τ_t represents year fixed effects to account for time variations, and ε_i is the error term, clustered by year and province.

The results are presented in Table 2. Regression (1) indicates a negative association between mental accounting and participation in risky assets. Specifically, individuals with mental accounting bias are 3.5% less likely to participate, a statistically and economically significant effect that represents a 12% relative decrease in participation compared to non-biased individuals. This finding aligns with theoretical predictions that mental accounting helps explain non-participation in risky markets.

However, examining participation at a more granular level by asset class provides a more nuanced picture. While mental accounting appears to discourage overall participation in risky assets, columns (4)–(6) reveal a positive association with cryptocurrency investment. The estimates suggest that individuals with mental accounting bias are 1% more likely than their unbiased counterparts to invest in cryptocurrencies. Given the low baseline participation, this translates to a 30% relative increase. In contrast, Column 7 shows a significant negative relationship between mental accounting and individual stock ownership, with participation rates 230 basis points lower.

[8]Due to the generally low participation rates in the Netherlands, I use a logit model rather than a probit model. The logit model's slightly fatter tails allow for a better fit when modeling lower probabilities.

Similarly, Column 10 documents a 270-basis-point decline in mutual fund participation. These findings suggest that mental accounting not only contributes to non-participation in risky markets but also influences asset preferences among those who do participate. These participants favor high-volatility, high-return assets like cryptocurrencies over lower-risk investments such as stocks and mutual funds.

Although the regressions include basic demographic controls, one concern is whether the results might capture other behavioral factors, particularly financial literacy and risk tolerance. To address this, I augment the regression with variables for high risk tolerance and financial literacy. Columns 2, 5, 8, and 11 show that including these controls does not alter the magnitude, statistical significance, or economic relevance of the results. This suggests that financial literacy and risk tolerance do not drive the observed effects; even when these factors are held constant, mental accounting remains an important determinant of participation decisions.

In additional tests (columns 3, 6, 9, and 12), I include wealth as a control variable. Unlike income, wealth is a computed measure, and due to limitations in the dataset's coverage of invested amounts,[9] including it reduces the number of observations. This constraint explains why wealth is excluded from the main specification. When wealth is included, the coefficient for cryptocurrencies increases, while those for stocks, mutual funds, and overall participation shift slightly in a more positive direction. This suggests that wealthier individuals, regardless of mental accounting bias, are more likely to invest across asset classes because they have greater investable resources. Regardless, the direction and statistical significance of the coefficients remain consistent. Additional specifications controlling for marital status, number of children, urbanization, and optimism yield no meaningful changes in the results. They are reported in the Appendix.

[9] See Alessie, Hochguertel, and Van Soest (2002) for a discussion on dataset limitations.

4.2.1 Heckprobit Model

A key challenge in analyzing the relationship between mental accounting and investment decisions is distinguishing between two related but distinct choices: (1) whether to participate in risky financial markets at all and (2) which asset classes to invest in once participation occurs. Standard regression models may fail to distinguish between these decisions, leading to imprecise estimates of which part of and to what extent the decision process is influenced by key variables such as mental accounting.

To address this, I estimate a Heckprobit model, which explicitly separates these two decisions. The first stage models the participation decision using a selection equation that includes an exclusion restriction: the average participation rate in the individual's province. Prior research on peer effects suggests that local participation rates influence an individual's likelihood of investing, as individuals are more likely to enter financial markets when surrounded by peers who participate (Hong, Kubik, and Stein, 2004; Brown, Ivković, Smith, and Weisbenner, 2008). Since provincial participation rates affect the probability of investing but should not directly influence which assets individuals choose once they have entered financial markets, this serves as a suitable exclusion restriction.[10]

The second stage then examines asset class selection conditional on participation. This approach allows me to determine whether mental accounting influences asset allocation beyond its effect on the participation decision itself. If mental accounting remains a significant predictor of asset selection after I correct for selection effects, this would provide stronger evidence that it plays an important role not only in the participation decision but also in the asset class selection decision.

Panel B of Table 2 presents the results from the Heckprobit estimation. Consistent with the

[10]To ensure the validity of the exclusion restriction, I conducted robustness checks to confirm that provincial participation rates are not associated with participation in specific asset classes once the initial participation decision has been accounted for.

earlier findings, mental accounting has a negative effect on the participation decision, which means that individuals with this bias are less likely to invest in financial markets. Beyond the initial participation decision, mental accounting shows a positive and strongly significant effect on holding cryptocurrencies, suggesting that individuals who do participate despite exhibiting mental accounting bias are more inclined to select high-risk, high-return assets. In contrast, mental accounting has a negative effect on holding either stocks or mutual funds, though the magnitude of this effect is smaller. This weaker effect is expected, as stocks and mutual funds have the highest general participation rates, which means that much of the reduced participation due to mental accounting is already captured in the first-stage selection equation.

These results provide further evidence that individuals with mental accounting bias are generally less likely to participate in financial markets. However, among those who do invest, there is a clear preference for high-risk, high-return assets like cryptocurrencies over traditional investments such as stocks and mutual funds. This pattern suggests that mental accounting not only discourages overall participation but also shapes investors' asset preferences once they enter the market.

5 Conditional Hypothesis

My results in the previous section provide initial empirical support for the role of mental accounting in investment decisions. Specifically, individuals who exhibit mental accounting bias are less likely to participate in financial markets overall, but those who do invest are more likely to hold high-risk, high-return assets like cryptocurrencies and less likely to invest in traditional assets like stocks or mutual funds. While these findings align with theoretical predictions, they leave out two important components of the model. First, they do not establish whether both tendencies —

i.e., rejecting lower-risk assets (G_S) and accepting higher-risk assets (G_L)—occur simultaneously. This distinction is crucial, as focusing on these decisions separately leaves out important aspects of the mechanism. For example, modeling only the rejection of G_S can be misleading, as this behavior can easily be replicated by assuming sufficiently high loss aversion. However, such high levels of loss aversion would also predict the rejection of G_L, which contradicts the observed behavior in Barberis et al. (2006). At the same time, modeling only the acceptance of G_L with sufficient risk tolerance would imply acceptance of G_S as well. Therefore, to empirically validate the behavior observed in the experiments, it is necessary to demonstrate that investors simultaneously reject G_S and accept G_L. In my empirical setting, this is represented by holding only cryptocurrency. Therefore, in this part of the analysis, I distinguish between individuals who invest exclusively in cryptocurrencies and those who hold both cryptocurrencies and traditional assets. If Hypothesis H2 holds, mental accounting should have a stronger effect on exclusive cryptocurrency investment than on mixed portfolios, as this best reflects the simultaneous acceptance of G_L and rejection of G_S. I estimate the following models:

$$\text{Holding Only Crypto}_i = \alpha + \beta_1 \text{MentalAccounting}_i + +CX_i + \tau_t + \varepsilon_{prov,t} \tag{2}$$

$$\text{Holding Crypto and Traditional Assets}_i = \alpha + \beta_1 \text{MentalAccounting}_i + CX_i + \tau_t + \varepsilon_{prov,t}. \tag{3}$$

As an additional reference, I run the same regression using traditional asset participation (stocks or mutual funds, without cryptocurrency) as the dependent variable. To ensure that I isolate the effect of mental accounting on asset class selection rather than general participation, I restrict this analysis to individuals who participate in financial markets. This allows me to focus specifically on how investors allocate their portfolios, conditional on participation.[11]

[11]When I apply this regression to the full sample, which includes non-market participants, the impact of mental accounting is also most pronounced among individuals who invest exclusively in cryptocurrencies.

The results, presented in Table 3 (Column 3) show that conditional on participation, mental accounting is associated with a 3.8 percentage point increase in the probability of holding only cryptocurrencies, which corresponds to a 54.6% relative increase compared to the baseline probability of holding only cryptocurrencies among individuals who do not exhibit mental accounting. In contrast, the effect is weaker in regression (5) which examines individuals who hold both cryptocurrencies and traditional assets, with a 2.1 percentage point decrease. Consistent with the Heckprobit results in section 4 , the coefficient in column (7) indicates that mental accounting has a negative but weaker effect on the selection of traditional assets, as much of this effect is already absorbed during the initial participation decision. However, the estimate remains strongly significant, with mental accounting associated with a 6.7 percentage point decrease in the probability of holding only traditional assets, representing a 9% relative decline conditional on participation. These findings further support the mechanism that mental accounting is crucial for explaining both the simultaneous rejection of G_S, i.e., non-participation in traditional assets, and the concentrated investment in high-risk assets (acceptance of G_L).

Moreover, general risk tolerance has no significant effect on exclusive cryptocurrency investment but is positively associated with holding both traditional assets and cryptocurrencies. This not only confirms that mental accounting—rather than risk tolerance—is driving the all-crypto investment pattern, but also rules out an important alternative explanation: that individuals invest in cryptocurrencies for risk diversification purposes or to add additional risk to their portfolios. While this may be true for some individuals, it does not apply to those with mental accounting bias, as they are more likely to concentrate their assets solely in cryptocurrencies, and risk tolerance has no significant explanatory power in accounting for this behavior.

5.1 Including Loss Aversion

The second key component of the Barberis, Huang, and Thaler (2006) framework that needs to be further considered is loss aversion. While Kouwenberg and Dimmock (2005) emphasize the role of loss aversion in explaining non-participation, they treat mental accounting as given and do not test its empirical relevance. Moreover, Kouwenberg and Dimmock (2005) focus only on the decision not to participate (rejecting G_S); therefore, we do not know the role loss aversion plays in the other crucial decision in this framework—namely, the acceptance of G_L. It is therefore important to include both components in the model to examine their distinct roles in explaining the observed behavior. Including both loss aversion and mental accounting in the regression estimation will allow me to assess whether the two components are complementary or act as substitutes in explaining the observed behavior, and to disentangle the specific role each one plays within the underlying mechanism. To empirically identify the distinct and complementary roles of mental accounting and loss aversion, I estimate the following models:

$$\text{Participation}_i = \alpha + \beta_1 \text{MentalAccounting}_i + \beta_2 \text{LossAverse}_i + CX_i + \tau_t + \varepsilon_{prov,t} \tag{4}$$

$$\text{Holding Only Crypto}_i = \alpha + \beta_1 \text{MentalAccounting}_i + \beta_2 \text{LossAverse}_i + CX_i + \tau_t + \varepsilon_{prov,t} \tag{5}$$

LossAverse is measured as a binary indicator for reporting a low tolerance for losses. I also estimate these models with alternative outcomes: holding both cryptocurrency and traditional assets, and holding only traditional assets. The results, presented in Table 3, show that loss aversion is negatively associated with participation in risky markets (Column 2). Among those who do participate, loss aversion is positively associated with holding only cryptocurrencies (Column 4) and negatively associated with holding both cryptocurrencies and traditional assets (Column 6), as well as with holding only traditional assets (Column 8). These findings suggest that loss-averse individuals are less likely to participate in risky markets. When they do invest, however, they tend to concentrate in high-return assets like cryptocurrencies, possibly because the high upside is perceived as sufficient to justify the risk of loss. In contrast, the moderate gains of traditional assets may not offer enough compensation to overcome their loss aversion.

Importantly, mental accounting remains strongly significant across all specifications. While loss aversion has a larger marginal effect on the non-participation decision, mental accounting is also strongly significant and improves model fit. A Wald test confirms its importance ($\chi^2(1) = 17.38$ and $p < 0.001$). Model selection criteria further support this result: adding mental accounting lowers both AIC and BIC by more than 10 points,[12] providing strong evidence in favor of the more complex model. Thus, although loss aversion plays a more dominant role in explaining non-participation, mental accounting offers complementary explanatory power and should not be omitted.

When I focus on asset class selection among participants, mental accounting appears even more important. While loss aversion continues to play a role, its relative influence declines. In regressions predicting whether individuals hold only crypto, both asset types, or only traditional assets, mental accounting consistently shows a strong and statistically significant effect, often rivaling or exceeding that of loss aversion.

To verify that mental accounting and loss aversion capture distinct behavioral traits, I regress the mental accounting indicator on loss aversion and relevant controls.[13] The coefficient on loss aversion is not statistically significant, and the correlation between the two variables is negative and close to zero (-0.014). This suggests that loss-averse individuals are not systematically more likely to exhibit mental accounting behavior. The two appear empirically unrelated, reinforcing the view that they operate through different psychological mechanisms. Therefore, it is appropriate

[12] AIC drops from 9397.331 to 9379.968, and BIC drops from 9491.465 to 9481.343.

[13] The results are available in the Appendix.

to include both variables in the participation and allocation models, as each captures a separate dimension of financial decision-making.

Although restricting the sample to participants should account for selection into market participation, I further test this using a Heckprobit model (Panel B). The results confirm that mental accounting has a consistently strong and significant effect on both the participation decision and the asset allocation decision. While loss aversion has a larger effect on participation, mental accounting becomes more influential in the second step, where investors choose which assets to hold. In this stage, the empirical importance of loss aversion diminishes, while the role of mental accounting increases. Under this specification, I also continue to find a stronger effect of mental accounting on investing exclusively in cryptocurrencies versus investing in mixed portfolios (cryptocurrencies and traditional assets).

5.2 Other Asset Classes

To further examine the effect of mental accounting on asset class selection based on risk and return preferences, I extend the analysis to additional asset classes. If mental accounting is indeed the underlying mechanism behind my main findings, similar patterns should emerge: increased participation in high-risk, high-reward assets, and decreased participation in lower-risk, lower-reward assets. I therefore examine bonds, real estate (excluding primary residences), and options. While these were excluded from the primary analysis due to limited observations, they remain valuable for exploring the broader implications of mental accounting. In my sample, 1.73% of participants hold individual bonds, 0.42% hold options, and 3.4% invest in real estate beyond their primary residence.

Bonds and real estate are typically considered lower-risk investments offering stable cash flows, albeit with limited capital appreciation relative to stocks. In contrast, options have become popular among retail investors as a low-cost method to leverage positions (Pavlova, 2023), primarily used for speculation rather than hedging. Based on these characteristics, I hypothesize that mental accounting will have similar effects on option holdings as it does on cryptocurrency, while its influence on bonds and real estate should mirror its effect on stocks and mutual funds.

I test this hypothesis using the logistic regression framework from the main analysis. The results, summarized in Table 4, show that mental accounting significantly reduces the likelihood of investing in bonds and real estate. The coefficient for options is positive but not statistically significant. Although including basic controls weakens some of the statistical significance, the negative effects on bonds and real estate remain robust. While low ownership rates of bonds and options limit the statistical power, the results are consistent with the theoretical predictions.

5.3 Ordered Logit

To further examine how mental accounting influences asset class selection along the risk–return spectrum, I estimate an ordered logit model that categorizes investors into four levels based on the risk-return profile of their portfolios. Level 1 consists of individuals holding only bonds or real estate, representing the lowest risk and lowest return. Level 2 includes those holding stocks or mutual funds, either alone or in combination with bonds or real estate, but not cryptocurrencies. Level 3 consists of individuals holding any of the aforementioned assets along with cryptocurrencies. Level 4 includes individuals holding only cryptocurrencies, representing the highest risk and highest return.

Figure 3 presents the marginal effects of mental accounting across these portfolio categories. The results show that mental accounting has the most negative effect on holding only low-risk assets, followed by a weaker negative effect on the second category, which includes stocks and mutual funds but excludes cryptocurrencies. The effect turns positive for portfolios that include both traditional assets and cryptocurrencies, with the strongest effect observed among individuals who hold only cryptocurrencies. The full results of the ordered logit model are provided in the Appendix. These findings further support the idea that mental accounting systematically influences asset class selection based on risk-return trade-offs.

6 Alternative Identification Strategies

6.1 Coarsened Exact Matching (CEM)

A key concern in interpreting the relationship between mental accounting and investment choices is that unobserved factors, such as risk tolerance, financial literacy, or income, could influence both the likelihood of exhibiting mental accounting and asset selection. While I control for these factors in all regressions, some unmeasured influences may still remain. To further isolate the effect of mental accounting, I employ Coarsened Exact Matching (CEM), a statistical technique that enhances causal inference by creating more comparable treatment and control groups based on key covariates. By reducing imbalance, this method ensures that any observed differences in investment behavior are more likely to be attributable to mental accounting than to other confounding factors.

For this analysis, I match individuals based on age, income quintile, education level, gender, risk tolerance, financial knowledge, and survey year. After matching, the analysis retains only observations where each individual exhibiting mental accounting is paired with a comparable individual who does not exhibit mental accounting but shares similar characteristics across the matched covariates. This approach ensures that differences in investment behavior can be more reliably attributed to mental accounting than to other underlying characteristics. Panel A in Table 5 reports the covariate balance between the treatment group ($Mental\ Accounting = 1$) and the control group

($Mental\ Accounting = 0$) by showing the means and mean differences with associated t-statistics. I report all the variables entering my matching specification. By construction, all the categorical covariates in the exact match are perfectly balanced. The continuous variables of age and income show no statistically significant differences between the treatment and control groups. As expected, matching on multiple variables slightly reduces the sample size, as only observations with a valid match are included. To account for potential differences between participation decisions and asset class selection, I conduct the analysis on both the full sample and the subsample of market participants.[14]

The results on the full sample, presented in Table 5, remain consistent with my main findings and are both statistically and economically significant. I continue to find a negative and highly significant association between mental accounting and overall participation in risky markets. Regarding asset class selection, mental accounting remains positively associated with holding cryptocurrencies and options, reinforcing the preference for high-risk, high-return asset classes. The negative relationship between mental accounting and low-risk, low-return assets also remains robust, as I continue to find a negative association with holding individual stocks, mutual funds, bonds, and real estate. The sizes of the coefficients are very close to those of my main specification and demonstrate that even when I compare individuals with similar demographics, economic conditions, risk tolerance, and financial knowledge, mental accounting continues to play a significant role in shaping both participation decisions and asset class selection.

6.2 Instrumental Variable Analysis

To further strengthen the identification of mental accounting's effect on asset class selection, I employ an instrumental variable (IV) analysis. The objective is to find a source of exogenous varia-

[14]Table 5 presents the results for the full sample, while the results for market participants are provided in the Appendix.

tion that influences the likelihood of exhibiting mental accounting but does not directly affect asset class selection. For this purpose, I utilize a unique survey question that asks individuals about the assignment of pocket money they received from their parents during childhood. The underlying intuition is that children who received pocket money early on may have learned to mentally separate budgets, distinguishing between necessary expenses such as food and clothing and discretionary spending from their allowance. This behavior closely mirrors the mental accounting framework used in adulthood. An extensive line of literature shows that early-life financial experiences shape long-term financial behaviors (Malmendier and Nagel, 2011, 2016; Malmendier, Tate, and Yan, 2011). If individuals learned to mentally separate budgets in childhood, they may be more likely to develop mental accounting tendencies that persist into adulthood.

A potential concern with this instrument is that receiving pocket money may be correlated with family economic status. If children from wealthier households were more likely to receive pocket money, they may also have had greater access to financial education and investment resources, which could later influence their investment choices. To address this concern, I restrict the analysis to a subsample of market participants, ensuring that all individuals in the sample are already actively investing. By focusing only on those who are already risky market participants, I reduce the likelihood that childhood economic background is driving the results. Among this group, receiving pocket money should not directly influence asset class selection, which makes it a more valid instrument for isolating the effect of mental accounting. To perform the instrumental variable analysis, I create a dummy variable, Child Allowance, which equals one if the individual received pocket money regularly during childhood. Table 6 presents the results of the instrumental variable estimation. Column 1 shows the first-stage results, which indicate that receiving pocket money as a child is positively and significantly associated with exhibiting mental accounting bias. The Cragg-Donald Wald F-statistic is 18.76, which exceeds the Stock-Yogo 10% critical value of

16.38 and confirms that the instrument is sufficiently strong.

Column 2 presents the second-stage results, where the likelihood of exhibiting mental accounting, predicted by the exogenous variation in Child Pocket Money, is positively and significantly associated with investing in cryptocurrency. Column 3 shows a negative association with holding individual stocks. Columns 4 through 7 report findings consistent with my main analysis, where mental accounting remains negatively associated with lower-risk, lower-return assets such as mutual funds, bonds, and real estate, and positively associated with high-risk, high-return assets such as options.[15]

These findings reinforce the role of mental accounting as a key determinant in asset class selection. They also provide additional evidence that mental accounting is a stable and persistent trait, as early-life financial experiences appear to shape long-term investment behavior. By establishing a link between childhood financial habits and adult asset selection, this analysis further strengthens the argument that mental accounting is not merely a contextual or situational bias but rather a fundamental cognitive framework that influences financial decision-making.

7 Consistency

7.1 Consistency over Time

To fully understand the implications and dynamics of my findings and therefore mental accounting, a key question must be addressed: Is this bias a persistent behavioral trait, or does it fluctuate in response to external conditions? It is essential to investigate its temporal stability at both the individual and population levels. If mental accounting is consistent over time, it would suggest that this bias is a core part of decision-making. However, if it is transitory, its effects might

[15] The association with mutual funds is insignificant in this test, but the coefficient remains in the expected direction, consistent with the main results.

be limited to certain contexts, which would have important implications for how we interpret the results of this study and apply the theoretical models underpinning it. Stability is a critical factor in behavioral research. Stigler and Becker (1977) assert that for a characteristic to be meaningful, it must exhibit consistency over time. Without such stability, it is more challenging to model, measure, and predict how a bias impacts behavior, particularly in the contexts of consumer choice and financial decision-making.

To investigate the temporal stability of mental accounting, I begin by examining the bias at the population level. By plotting the mental accounting variable over the years, as shown in Figure 4, I observe that the proportion of individuals exhibiting this bias remains remarkably stable over time. This finding aligns with the work of Stango and Zinman (2020), who also show that most behavioral biases, including mental accounting, tend to be stable both across the population and within individuals.

To assess stability at the individual level, I extend my main analysis by restricting the sample to individuals who participated in all five waves of the survey, which results in a final sample size of 1,348 individuals. I then create a new mental accounting dummy variable, assigning a value of 1 only if the individual demonstrates mental accounting tendencies in each of the five waves in the sample. My dependent variable is a binary indicator equal to 1 if the individual invested in cryptocurrency at any point during the sample period. Since the survey asks about participation in the prior year, the 2019 wave inquires about cryptocurrency holdings as of the end of 2018. I average the main control variables across the sample period to account for consistency in the covariates. My final model is as follows:

$$\text{Invest in Crypto}_{2018\text{–}2022} = \alpha + \beta \cdot \text{Consistent Mental Accounting}_{2018\text{–}2022} + CX_{\text{Avg Controls}} + \varepsilon \quad (6)$$

Table 7 presents the results, showing that my findings remain consistent even when I apply this alternative approach. Notably, I do not find a significant effect when examining individuals who switch from not exhibiting mental accounting to exhibiting it (i.e., "switchers"). This suggests that the observed effects associated with mental accounting come from a stable cognitive characteristic rather than a behavior that individuals transition into and out of over time.

7.2 Market Exit

To further reinforce the coherence of my findings, I examine the behavior of individuals who exited the cryptocurrency market in the past year. If mental accounting bias leads investors to either avoid financial markets entirely or concentrate their portfolios in high-risk, high-return assets, then those who previously held only cryptocurrencies should be more likely to fully exit the market rather than rebalancing their investments into other asset classes. On the other hand, individuals who had exposure to both cryptocurrencies and traditional assets may be more inclined to shift their investments back into traditional assets rather than withdrawing from the market altogether.

Figure 6 supports this pattern. Among those who exited the cryptocurrency market, most investors who had held only cryptocurrencies fully withdrew from financial markets. This result aligns with the idea that they either invest in speculative assets or do not participate at all. In contrast, those who had previously invested in a mix of cryptocurrencies and traditional assets were more likely to rebalance into other asset classes than to leave the market. This observation highlights the consistency of the mechanism, as the patterns persist even after individuals enter the market: they show limited movement toward lower-risk assets and prefer to exit the market altogether.

7.3 Extension to Individual Stock Selection

One potential challenge to the coherence of my findings is that, while stocks and mutual funds are broadly categorized as lower-risk, lower-return assets, investors can still take on significant risk within these asset classes by selecting highly volatile individual stocks or high-risk mutual funds. If mental accounting bias drives investors toward high-risk, high-return investments, then an important question is whether this bias also influences stock selection among those who do choose to participate in the stock market. While the findings from other asset classes already provide some evidence against this concern, a more granular analysis of individual stock selection can further clarify whether mental accounting leads investors to favor riskier stocks in line with the broader pattern observed across asset classes.

While mental accounting explains non-participation in the stock market, other theoretical frameworks explore how this bias might affect stock selection among investors who do choose to participate. Barberis and Huang (2001) propose that individuals with mental accounting bias shift their discount rate for a particular stock based on the asset's past performance. Specifically, when a stock has performed well recently, the investor derives utility from the gain and becomes less concerned about potential future losses, perceiving the stock as less risky. Conversely, after poor performance, the investor perceives greater risk, which leads to more extreme price movements. This theory implies that investors with mental accounting bias may favor stocks with more extreme returns and higher volatility. To test this, I examine whether, conditional on holding individual stocks, these investors are more likely to select stocks with higher volatility and more extreme past returns.

7.3.1 Individual Portfolio Data

To measure the impact of mental accounting on individual stock selection, I leverage a unique aspect of the DHS survey: participants are asked to list the companies in which they hold individual shares. I manually match these company names to their respective stock tickers and retrieve return data from Yahoo Finance, focusing on the 2018–2022 period to align with my sample data. I also perform the analysis over longer time frames and find consistent results. Although this dataset is less precise—due to incomplete or unclear responses—and I lose some observations, I manage to obtain individual stock holdings for 727 individuals. Due to inconsistencies in the reported sizes of these positions, I assume equal weighting across the portfolio and focus my analysis on the first three stocks named. I prioritize these for two reasons: first, people tend to mention the most significant positions first (Ley, 1972); second, the majority (approximately 75%) of my sample holds no more than three stocks, which aligns with findings in previous literature (Campbell , 2006). I first calculate the average annual returns and standard deviations for each stock at the individual level, and then compute the averages of these measures at the portfolio level. Next, I rank the participants' portfolios by deciles, examining whether mental accounting influences the likelihood of being in the upper or lower decile in terms of mean returns. Additionally, I assess the likelihood of being in the top two deciles of average standard deviation.

To explore how mental accounting might affect the optimality of investment decisions, I also calculate the Sharpe ratio for each investor's portfolio. This allows me to assess whether investors influenced by mental accounting select stocks with better or worse risk-adjusted returns.The main findings are reported in Table 8. I find that mental accounting is positively and significantly associated with holding stocks that yield more extreme returns and bear higher risk. Although higher risk and return could be justified by superior risk-adjusted returns, investors influenced by mental accounting do not appear to make optimal stock selections, as mental accounting is associated with choosing stock portfolios that, on average, exhibit a 0.1 lower Sharpe ratio. These results suggest that mental accounting not only affects asset class selection but also plays a significant role in the financial decisions made within asset classes, particularly in individual stock picking.

7.4 Alternative Measure

A common challenge in survey-based research is the potential for measurement error, as self-reported responses may be affected by inattentiveness, misinterpretation, or inaccurate reporting (Krosnick, 1991; Kaminska et al., 2010; Herzog and Bachman, 1981). This raises concerns about the reliability of my primary mental accounting variable, which is constructed from survey responses. If respondents do not accurately report their financial behavior or fail to fully understand the survey questions, the measurement of mental accounting may be noisy or biased, potentially affecting the robustness of my findings.

To address this concern, I incorporate an alternative measure of mental accounting based on the number of checking accounts an individual holds. This approach is motivated by insights from the consumption literature (Thaler, 1999), which suggests that individuals who engage in mental accounting often maintain separate checking or savings accounts for different purposes, such as fixed expenses, discretionary spending, or savings. By relying on this observed financial behavior rather than self-reported survey responses, this alternative measure reduces the risk of measurement error and reporting biases that may affect direct survey-based assessments of mental accounting.

First, I verify that my mental accounting variable correlates with individuals holding a larger number of personal checking accounts, thereby assessing whether the survey question effectively captures mental accounting practices. Second, I use the number of checking accounts as an alternative measure of mental accounting and repeat my main analysis. Several concerns may arise with this approach. One concern is that individuals might hold multiple checking accounts because they have more funds to deposit. Another is that they might use multiple accounts for liquidity management purposes. To address these issues, I control for the total amount held across all checking accounts. Additionally, I repeat the analysis after excluding observations where the total amount in checking accounts exceeds the €100,000 threshold protected by the Dutch Deposit Guarantee Scheme (DGS), which is the maximum amount insured per person per bank. [16] A third concern is that some checking accounts may have been opened by parents or may be shared with a spouse, which could confound the analysis. To mitigate this, I include only accounts that are solely in the individual's name and exclude any joint or parental accounts from the dataset.

I present my analysis in Table 9. The sample size is smaller than in the main analysis due to incomplete reporting of the amounts held in checking accounts. In Column 1, I find that the mental accounting variable is strongly and positively associated with the number of personal checking accounts an individual holds. Columns 2 and 3 show that neither the total amount held in checking accounts nor the level of financial knowledge alters the significance or coefficient of this relationship. In Column 4, I replicate my main analysis and test the effect of the number of checking accounts on the likelihood of investing in cryptocurrency, finding a significant positive association consistent with my primary results. The statistical power is weaker than in the main analysis, which is expected since the number of checking accounts serves only as a proxy for mental accounting.

These results further support the robustness of my findings by demonstrating that responses to the survey question translate into actual financial behavior. By showing that individuals who report mental accounting tendencies also hold more checking accounts for separate purposes, I validate the survey question as a reliable measure of mental accounting practices.

[16] It is important to note that in the Netherlands, checking accounts are primarily used for managing daily expenses, making payments, or withdrawing cash. Moreover, the proportion of extremely wealthy individuals is much lower in the Netherlands than in the United States; therefore, few individuals have over €100,000 in their checking accounts.

8 Additional Tests and Robustness

8.1 Other Behavioral Factors

To further test the robustness of my findings and rule out alternative explanations, I examine other behavioral factors that may influence asset class selection. Prior research shows that traditional investors already differ from the general population (Campbell, 2006; Grinblatt and Keloharju, 2001; Barber and Odean, 2001; Hong, Kubik, and Stein, 2004; Guiso, Sapienza, and Zingales, 2008), so differences between cryptocurrency investors and the general population are expected. The more informative comparison is between cryptocurrency and traditional investors. I therefore test for behavioral differences between, traditional investors and cryptocurrency investors.[17] I examine three categories of behavioral factors that have been shown to influence financial decisions: risk preferences (Hoffmann et al., 2013; Guiso and Paiella, 2008), cognitive orientation, which includes optimism, locus of control, and time horizon (Cobb-Clark et al., 2016) and financial knowledge (Lusardi et al., 2011; Ke, 2021).

For risk preferences, beyond the general risk tolerance and loss aversion already addressed in my analysis, I consider two additional variables: Preference for Leverage and High Risk Taken. Preference for Leverage assesses the tendency toward gambling behavior, as the use of leverage is associated with compulsive gambling (Cox et al., 2020). High Risk Taken explores the actual risk engagement by measuring the investor's perception of the risks they have undertaken. This tests whether crypto investors are aware of the risk they take and whether the perceived risk taken matches their risk tolerances. More detailed descriptions of these variables are in the appendix.

I employ logistic regression to assess how these behavioral variables affect the likelihood of investing in cryptocurrencies versus traditional asset classes. The binary dependent variable is

[17] I also run these tests comparing cryptocurrency investors and the general population, and I present these results in the Appendix.

assigned a value of 1 if the individual invests in cryptocurrencies and 0 if the individual invests exclusively in traditional assets.

Within the cognitive orientation category, I examine optimism, locus of control, and time horizon. The aim is to ascertain whether cryptocurrency investors, compared to stock investors, exhibit excessive optimism and whether this influences their choice of asset class. While it is challenging to isolate optimism about specific asset classes, I assess general levels of optimism using a survey measure that evaluates individuals' overall expectations of positive versus negative outcomes (see the Appendix for the specific question). Investors who express a high level of optimism are classified as optimistic.

Additionally, I analyze investors' time horizons to ensure that asset class selection decisions are not driven solely by short-term speculation. Assessing the locus of control helps me to discern any differences between cryptocurrency investors and stock investors regarding the degree of influence they believe they have over their financial success.

In addition to my primary measure of financial knowledge, I test an alternative approach following Ke (2021), who uses employment in the financial sector as an instrument for financial literacy. To capture this, I create an indicator variable equal to 1 if an individual is employed in the finance or business sector and 0 otherwise. This measure accounts for professional exposure to financial concepts that may influence investment decisions.

Table 10 presents the estimation results, which reveal no significant differences in risk preferences, cognitive orientation or financial knowledge between cryptocurrency investors and traditional investors. Further supporting this argument, I also examine the market timing of individuals with mental accounting tendencies and find that these align with mental accounting theory (Barberis and Huang, 2001) and not with the argument that these investors have private information or engage in strategic market timing.[18]. Notably, optimism is the only variable exhibiting a negative and statistically significant effect. To ensure that optimism does not confound my results, I re-estimate my main analysis while controlling for optimism. The findings remain unchanged.

8.2 Additional Robustness Checks

To account for other potential confounding factors, I perform a series of additional tests. I rerun the main analysis, adding control variables such as numeracy skills to address the possibility that individuals may not understand the mathematical concepts behind risk diversification, rather than exhibiting mental accounting bias. Additionally, I control for the financial education provided by the individual's family to further account for the financial background of the individual. Finally, I control for attention to cryptocurrencies by incorporating Google search volume for cryptocurrencies by province. Incorporating these controls does not alter the coefficients or the statistical significance of my findings. The consistency of the results, despite the addition of these variables, reinforces the validity of my conclusions regarding mental accounting and investment behavior. Detailed results of these tests are presented in the Appendix.

8.3 External Validity

While this study offers insights into how mental accounting influences participation and asset allocation decisions, it is important to assess the generalizability of these findings beyond the Dutch context and provide external validity on a global scale.

One significant factor influencing investment behavior is the pension system. The Netherlands has a robust and mandatory pension scheme, with one of the highest income-to-pension conversion rates at 93.2%[19]. This substantial safety net diminishes the necessity for Dutch individuals to

[18] A more detailed analysis can be found in the appendix

[19] The pension replacement rate of the Netherlands in 2022 according to oecd.org

fund retirement through their own investments, unlike in the United States where individuals bear a greater responsibility for their retirement savings. Moreover, the Netherlands offers subsidized college education, has generous maternity leave and parental support policies, and has ranked first in the Euro Health Consumer Index, which measures citizens' satisfaction with their healthcare system. These comprehensive social benefits lessen the need for personal savings to cover education, healthcare, and family support expenses.

Consequently, in the Netherlands investing is a supplemental means of saving, whereas in countries where these services are not provided, investing is a necessity for retirement planning or essential expenditures. This is consistent with the observation that for Dutch investors, cryptocurrency investments are more likely to be associated with saving goals like dividends, personal business ventures, or bequest motives, rather than unexpected expenses, children, or future liabilities, as reflected in Table 11. In contrast, in countries without extensive social support systems—such as the United States—mental accounting can still lead individuals to favor high-risk, high-reward investments as shown in the U.S.-based Kahneman and Tversky (1979) experiments. However, the necessity to save for retirement and other essential expenses may limit the proportion of investments allocated to high-risk assets like cryptocurrencies.

This implication aligns with the results of Weber et al. (2023), who finds that a lower proportion of investors in the U.S. exclusively hold cryptocurrencies; in contrast, statistics from the DHS indicate that a higher proportion of such investors exist in the Netherlands. Interestingly, Aiello et al. (2022) observed that U.S. investors used their stimulus checks, which could be considered supplemental funds, to invest in cryptocurrencies. While mental accounting may lead investors to favor cryptocurrencies, in countries with strong social systems, crypto and other high-risk, high-reward investments might constitute a large chunk of a biased investor's portfolio. In contrast, in countries with weaker social systems, the allocation might be lower due to the need to allocate resources toward retirement savings, college education, and healthcare. Further research on which specific mental accounts lead to particular investment behaviors could provide deeper insights. Gargano and Rossi (2024) highlight the effect of goal setting on investment behavior, underscoring the importance of understanding the interplay between mental accounting and investment choices.

Given these structural differences, other institutional and cultural factors may further shape how mental accounting influences investment behavior. Both the Netherlands and the United States take a cautious approach to cryptocurrency regulation, which suggests that regulatory constraints may similarly influence investor attitudes in both countries. Cultural factors, including gambling propensity, may further impact investment decisions. Gambling is more regulated and less prevalent in the Netherlands than in the United States, where higher gambling rates may translate into a greater willingness to engage in high-risk investments like cryptocurrencies (Kumar, 2009). This suggests that cultural differences in gambling are not confounding the results.

While the findings suggest that mental accounting influences asset allocation broadly, the degree to which it shapes investment decisions depends on the economic, regulatory, and cultural environment. Future research could further explore these interactions across different countries to refine our understanding of how mental accounting operates in varying institutional settings.

9 Discussion and Conclusion

This study examines how mental accounting influences both the participation decisions and asset class selections of individuals. I use a unique question in the Dutch National Bank Household Survey to identify individuals with mental accounting bias. I provide robust evidence that individuals exhibiting mental accounting bias are less likely to participate in financial markets. However, when they do invest, they tend to concentrate their portfolios in high-risk, high-return assets such as cryptocurrencies and options, and they are reluctant to invest in lower-risk investments like stocks, mutual funds, bonds, and real estate.

I also find that risk tolerance alone cannot explain this allocation decision once the initial risky market participation decision has been accounted for. My results hold even when I control for risk tolerance, financial literacy, socioeconomic factors, and demographic characteristics. They also remain robust across multiple identification strategies, including Heckprobit models, an instrumental variable analysis, and coarsened exact matching. Additionally, I find that mental accounting is a persistent trait over time and across different financial settings.

My findings align with theoretical predictions that mental accounting drives investors to focus on potential gains that compensate for their fear of losses while disregarding the diversification benefits of lower-risk assets. This leads investors to either concentrate their portfolios in speculative assets or refrain from participating in financial markets altogether.

This study is one of the first empirical investigations to provide individual-level evidence on how mental accounting shapes financial decisions. It not only validates existing theories with real-world data but also provides valuable insights for policymakers and practitioners. Recognizing mental accounting as a stable trait that significantly and persistently affects financial decisions across multiple settings highlights the importance of incorporating cognitive biases like mental accounting into financial decision-making models. By integrating mental accounting into traditional utility frameworks, we can better understand investor behavior and develop interventions to mitigate its effects.

This study also sheds light on why some investors favor certain asset classes over others, particularly when risk tolerance alone cannot explain their choices. Future research can build on these findings by exploring how mental accounting manifests in different contexts or by identifying additional mental accounts. A key question is whether mental accounting bias can be mitigated and, if so, whether such mitigation encourages investors to take a more holistic view of their wealth and investment portfolios, ultimately leading to better financial decisions.

Finally, these findings have important policy implications. Recognizing that risky investment behavior is not driven solely by risk tolerance can help regulators and financial practitioners design more effective tools to assist investors in making rational decisions. Acknowledging the role of mental accounting allows policymakers to create targeted strategies that promote balanced and informed financial choices. These strategies could include educational programs to raise awareness of cognitive biases or financial products that encourage diversified investment strategies.

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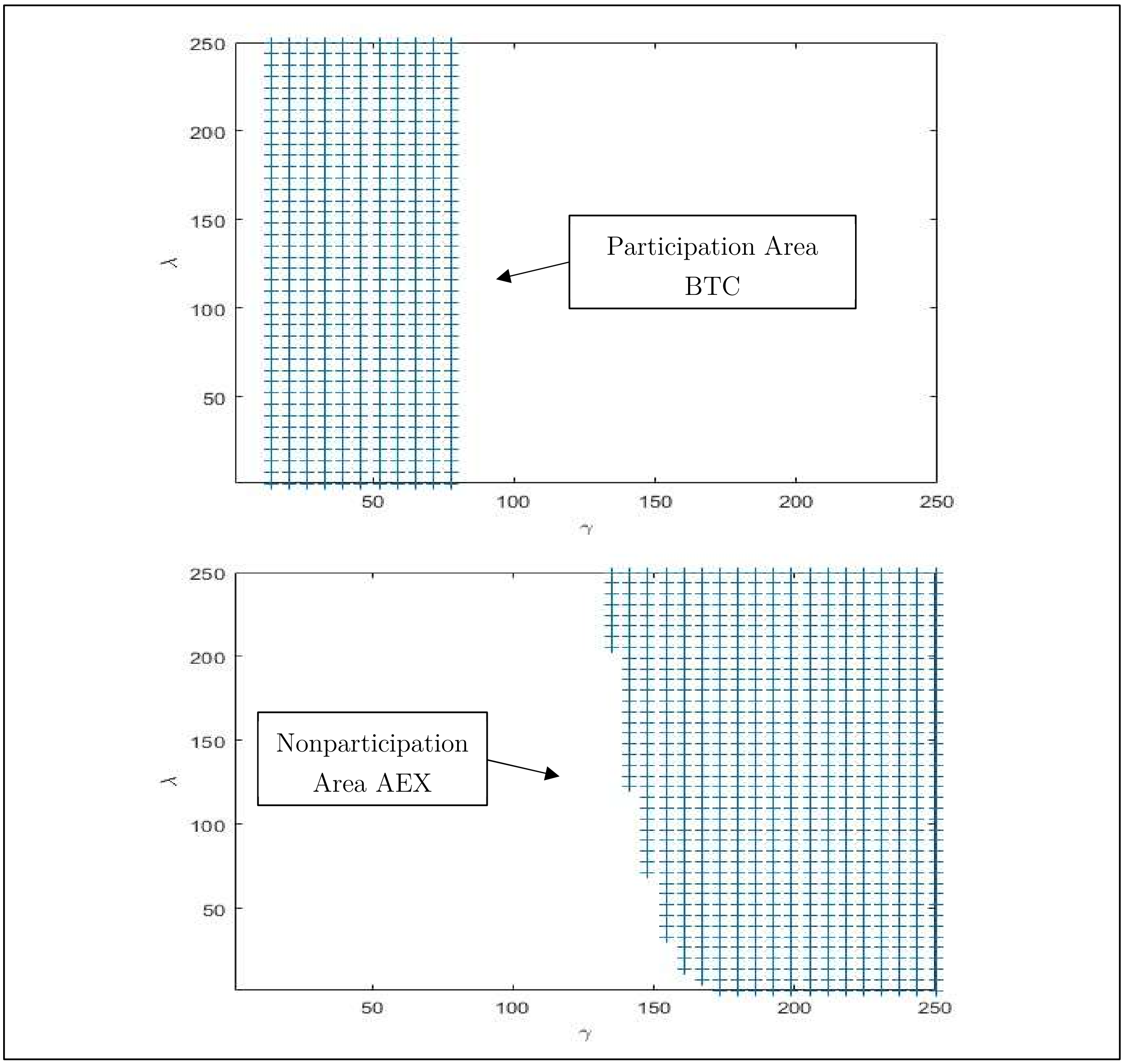
Figure 1: Simulation Results BTC and AEX

This Figure displays simulation results using statistical properties of BTC and statistical properties of AEX (Amsterdam exchange). Panel A illustrates, non-stock market participation and participation in BTC without narrow framing. Panel B displays the simulation results with mental accounting: the top area shows non-stock market participation, and below is participation in BTC with mental accounting. The parameter γ describes sensitivity to losses and λ describes risk aversion. BTC and AEX statistical properties are based on annual returns and standard

Panel A: Without Mental Accounting



Panel B: With Mental Accounting

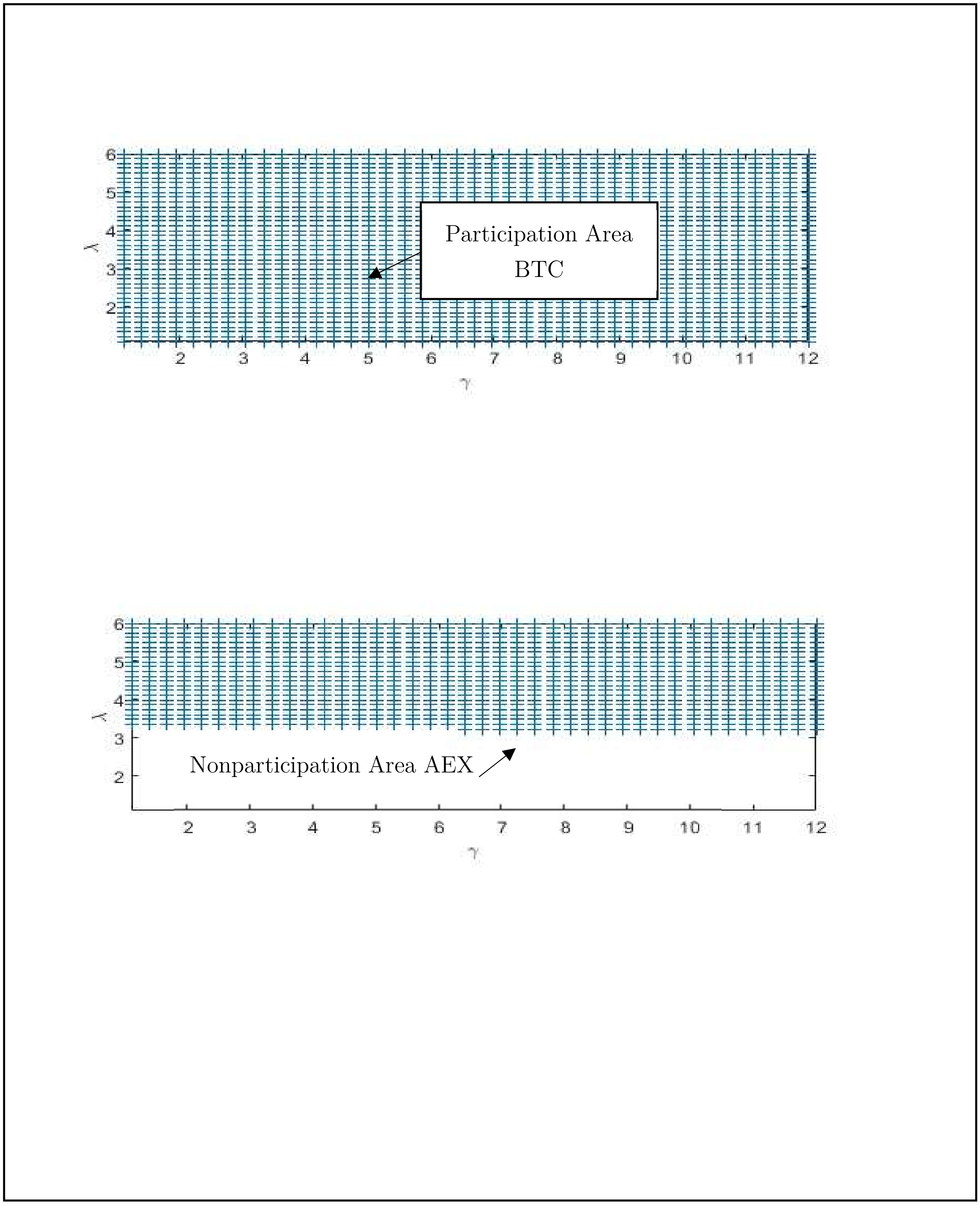


Figure 2: Investment Participation by Bias and Asset Category

This figure shows the difference from the full sample mean participation rate within each investment category: only cryptocurrencies, both cryptocurrencies and traditional assets, only traditional assets, and non-participation. Differences are shown separately for individuals with mental accounting bias and those without.

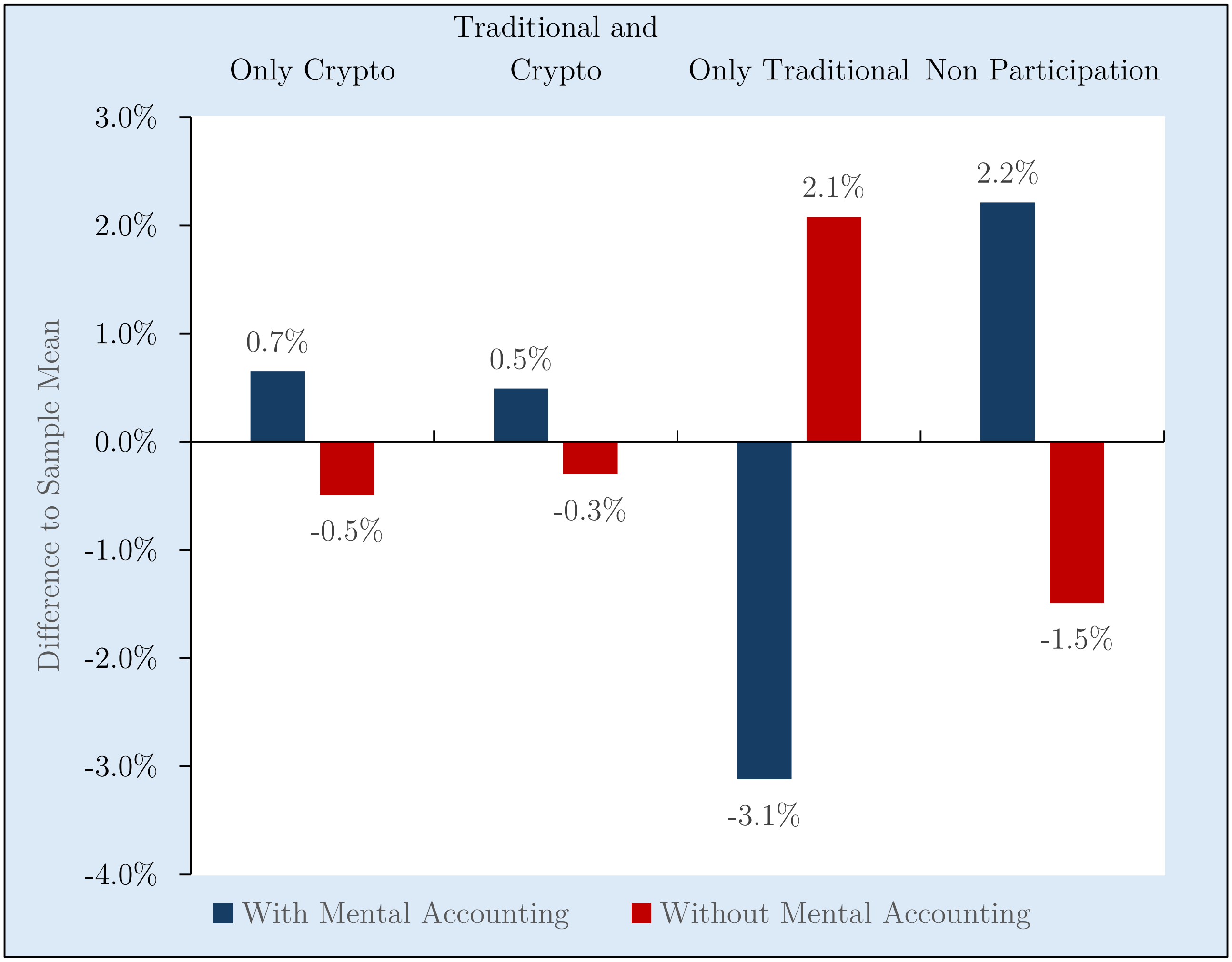


Figure 3: Ordered Logit Marginal Effect

This figure illustrates the marginal effects from the ordered logit model on the probability of participation in each asset class category, which are ordered by risk-return profile. The lowest risk-return category includes individuals holding only bonds or real estate, while the highest risk-return category consists of those exclusively holding cryptocurrencies. The figure shows how mental accounting influences the probability of belonging to each participation category, with changes in mental accounting redistributing probabilities across the ordered risk-return spectrum.

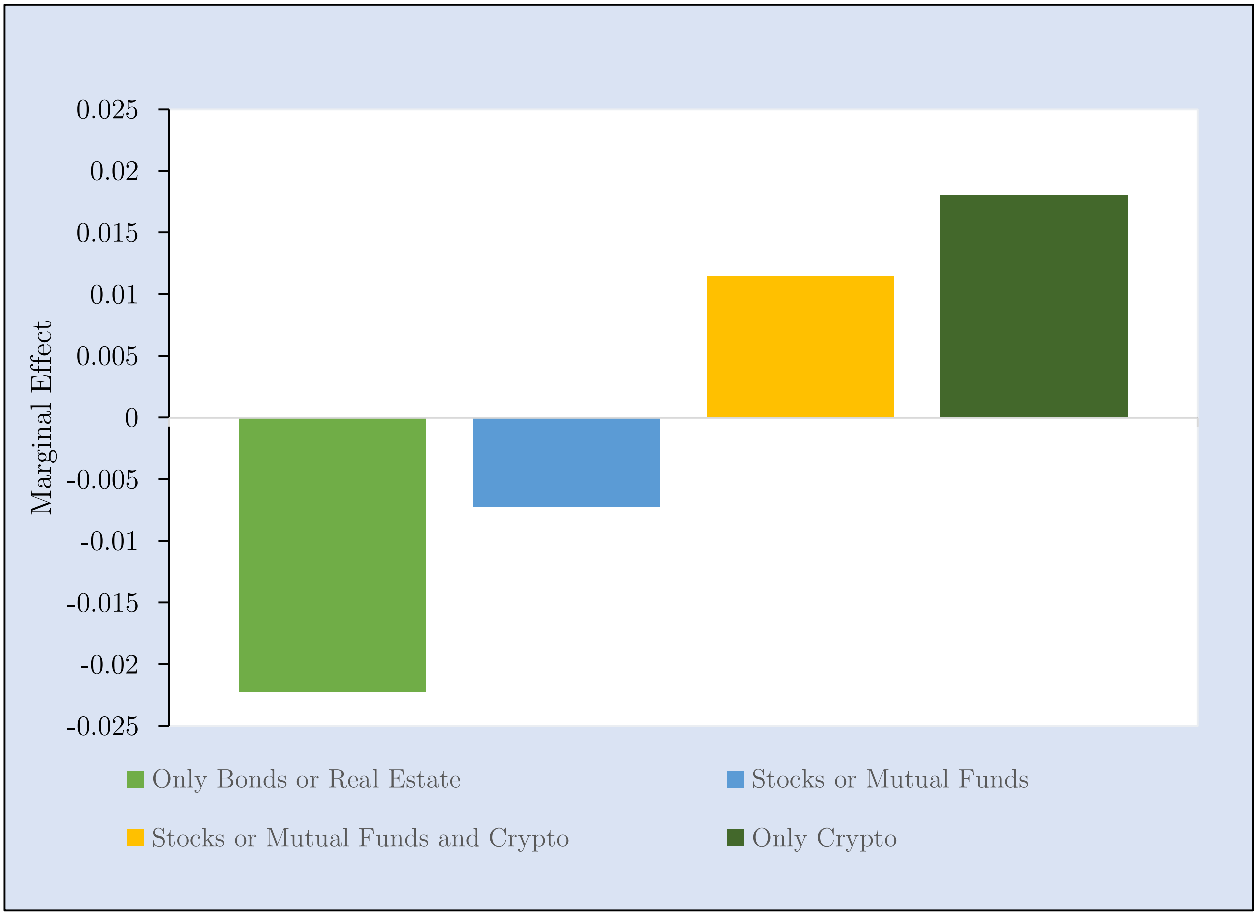


Figure 4: Annual Proportion of Investors Exhibiting Mental Accounting Bias

This figure presents the yearly proportions of investors exhibiting mental accounting bias for my sample period from 2019 to 2023.

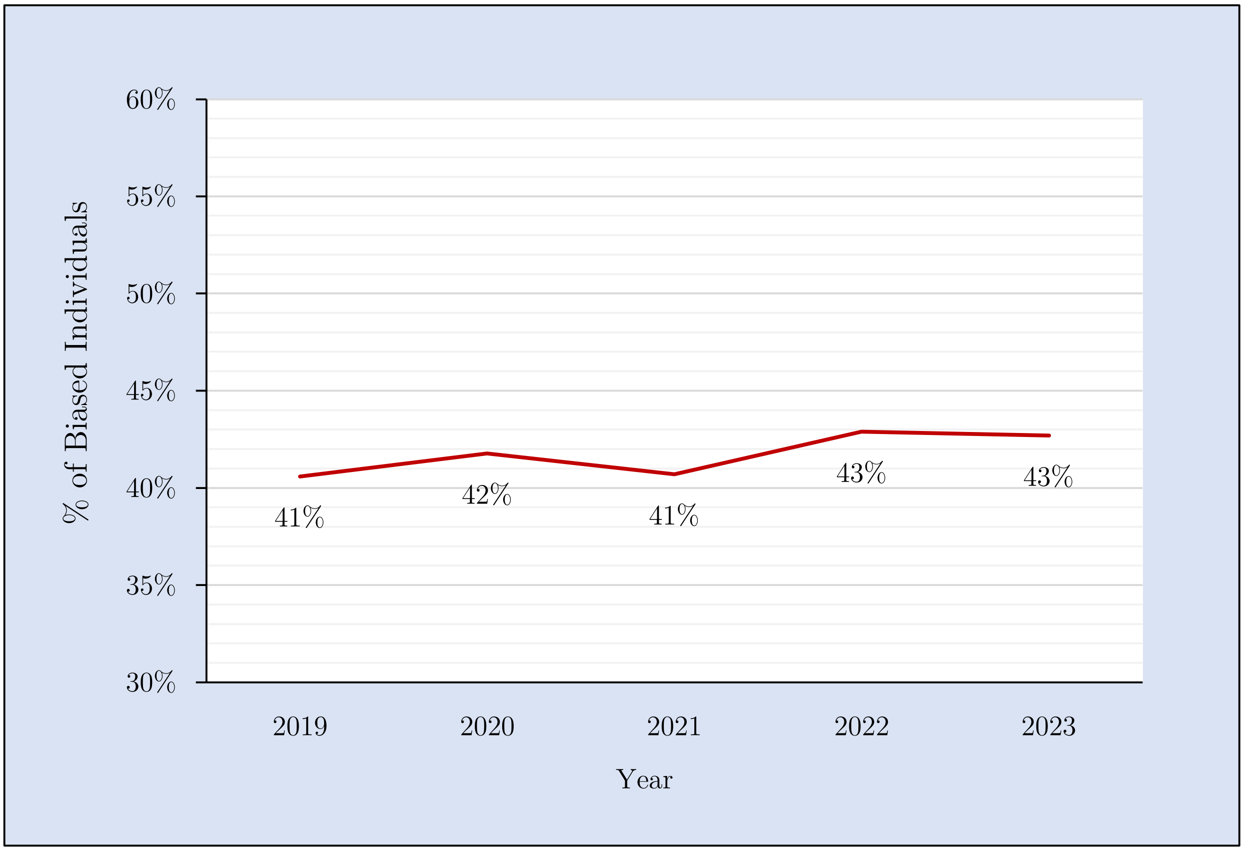


Figure 5: Exit Decisions

This figure illustrates the proportion of individuals who sold cryptocurrencies in the previous year and their investment status in the following year. Investors are categorized based on their prior holdings, where Crypto and Traditional (t-1) refers to individuals who held both cryptocurrencies and either stocks or mutual funds in the previous period, while Only Crypto (t-1) refers to individuals who exclusively held cryptocurrencies in the previous period. The figure distinguishes between two possible outcomes in the following year: Remain Participant indicates that the individual continues participating in financial markets by holding at least one asset class, such as stocks, mutual funds, bonds, real estate, or options, whereas Full Exit refers to individuals who completely exit financial markets and become non-participants.

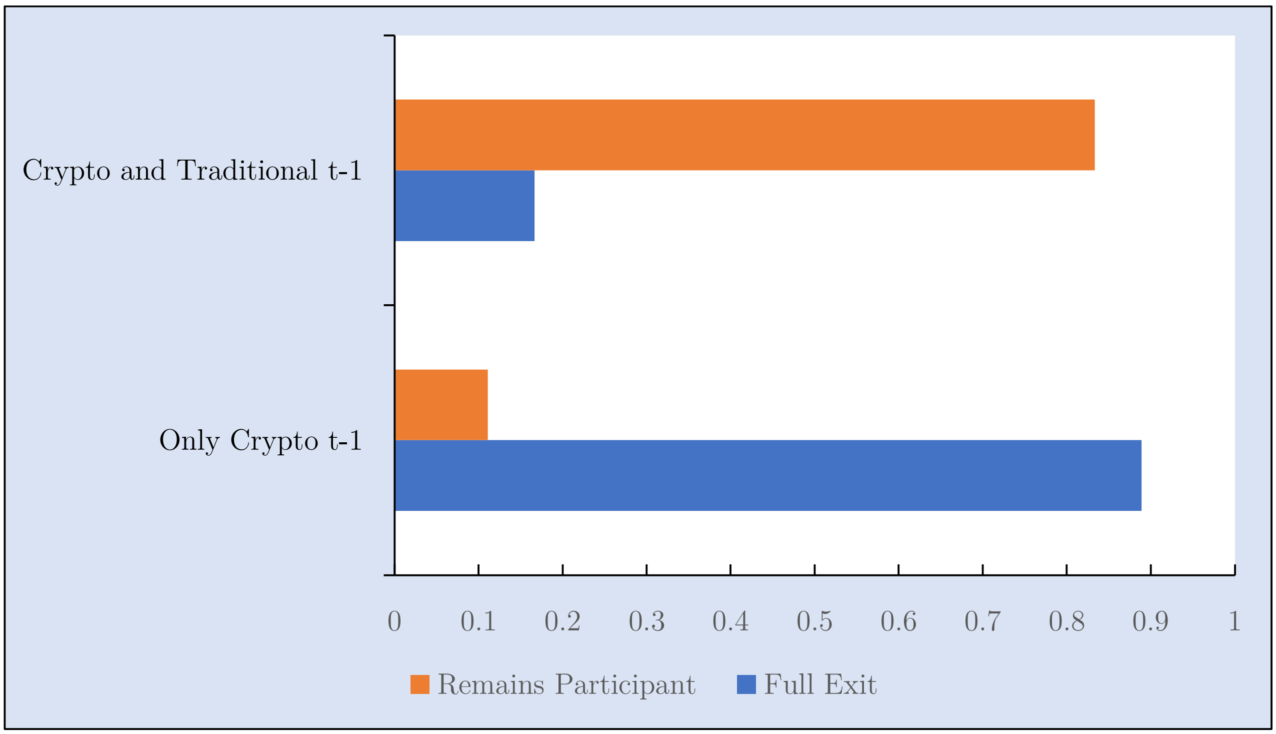


Table 1

Summary Statistics

This table contains summary statistics of the sample used in the empirical analysis and three subsamples of interest: Full Sample (Panel A), Crypto Investors (Panel B), Traditional Investors (Panel C), and individuals subject to Mental Accounting (Panel D). Table A.1 presents the definitions of all variables.

	Panel A: Full Sample			*Panel B:* Crypto Investors		
	N	Mean	St.Dev	N	Mean	T-Test
College	12,855	0.385	0.487	454	0.515	5.822
Gender	12,860	0.508	0.500	454	0.720	9.227
Income	12,860	39,819	33,914	454	45,460	3.610
Age	12,860	55	17	454	43	-15.652
Married	11,890	0.580	0.494	399	0.499	-3.353
Number Children	12,860	0.566	0.985	454	0.877	6.841
Urbanization	11,569	3.080	1.325	412	3.187	1.673
High Risk Tolerance	10,316	0.131	0.337	376	0.410	16.539
Financial Knowledge	12,560	2.281	0.762	439	2.622	9.578
Holds Crypto	12,860	0.035	0.185	454	1.000	.
Holds Stocks	12,860	0.089	0.285	454	0.282	14.782
Holds Mutual Funds	12,860	0.119	0.324	454	0.317	13.390
Holds Bonds	12,860	0.017	0.131	454	0.037	3.302
Holds Real Estate	12,860	0.034	0.182	454	0.059	3.028
Holds Options	12,860	0.004	0.062	454	0.042	13.323
Mental Accounting	12,560	0.415	0.493	439	0.549	5.808

Table 1 - Continued

	Panel C: Traditional Investors			*Panel D:* Mental Accounting		
	N	Mean	T-Test	N	Mean	T-Test
College	1,914	0.607	21.997	5,210	0.398	2.791
Gender	1,914	0.706	18.996	5,212	0.477	-6.574
Income	1,914	47,711	11.086	5,212	41,683	5.407
Age	1,914	59	10.547	5,212	52	-19.994
Married	1,756	0.596	1.427	4,885	0.580	-0.081
Number Children	1,914	0.445	-5.847	5,212	0.677	11.606
Urbanization	1,768	3.146	2.285	4,665	3.119	2.930
High Risk Tolerance	1,725	0.319	26.281	4,249	0.138	1.718
Financial Knowledge	1,881	2.571	18.136	5,212	2.323	5.216
Holds Crypto	1,914	0.000	-9.100	5,212	0.046	5.808
Holds Stocks	1,914	0.533	.	5,212	0.076	-4.358
Holds Mutual Funds	1,914	0.723	.	5,212	0.102	-5.109
Holds Bonds	1,914	0.083	24.050	5,212	0.014	-2.474
Holds Real Estate	1,914	0.072	9.952	5,212	0.029	-2.641
Holds Options	1,914	0.011	5.403	5,212	0.005	1.198
Mental Accounting	1,881	0.339	-7.300	5,212	1	.

Table 2

Mental Accounting and Asset Class Participation

Panel A reports the marginal effects from logistic regressions. In Columns (1)–(3), the dependent variable is participation, an indicator that takes on the value of 1 if the individual participates in any risky market (stocks, mutual funds, crypto, bonds, real estate, or options). In Columns (4)–(6), the dependent variable is cryptocurrency participation. In Columns (7)–(9), the dependent variable is individual stock ownership, and in Columns (10)–(12), the dependent variable is mutual fund participation. Panel B reports results from a Heckman probit selection model. The dependent variable in Column (1) is cryptocurrency participation, while the dependent variable in Column (2) is participation in either stocks or mutual funds. The selection equation estimates the likelihood of participating in risky markets. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A												
	Participation			Crypto			Individual Stocks			Mutual Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mental Accounting	-0.035***	-0.036***	-0.021**	0.010***	0.010***	0.011***	-0.023***	-0.023***	-0.021***	-0.027***	-0.027***	-0.019***
	(-4.11)	(-4.26)	(-2.45)	(3.41)	(3.38)	(3.54)	(-3.56)	(-3.56)	(-2.74)	(-4.40)	(-4.51)	(-2.97)
Risk Tolerance	0.228***	0.216***	0.211***	0.037***	0.035***	0.036***	0.121***	0.114***	0.119***	0.140***	0.131***	0.129***
	(21.62)	(20.56)	(20.87)	(8.05)	(7.66)	(7.35)	(15.90)	(14.53)	(13.47)	(23.25)	(21.49)	(20.08)
Financial Knowledge		0.055***	0.040***		0.009***	0.009***		0.030***	0.026***		0.038***	0.030***
		(12.58)	(8.55)		(4.20)	(3.56)		(7.64)	(5.85)		(10.06)	(7.73)
Log Wealth			0.077***			0.003**			0.021***			0.040***
			(28.69)			(2.10)			(9.89)			(16.70)
College	0.124***	0.115***	0.076***	0.005	0.003	-0.002	0.061***	0.055***	0.046***	0.096***	0.089***	0.074***
	(15.62)	(14.91)	(9.77)	(1.21)	(0.71)	(-0.37)	(10.23)	(9.85)	(7.99)	(13.60)	(13.19)	(9.99)
Gender	0.113***	0.101***	0.066***	0.031***	0.029***	0.028***	0.071***	0.063***	0.055***	0.054***	0.045***	0.023***
	(13.32)	(11.91)	(7.72)	(8.77)	(8.42)	(7.09)	(11.56)	(10.64)	(8.44)	(6.47)	(5.41)	(2.64)
Log Income	0.050***	0.045***	0.008	-0.002	-0.003	-0.005**	0.023***	0.020***	0.011**	0.040***	0.035***	0.017***
	(7.66)	(7.05)	(1.27)	(-0.77)	(-1.18)	(-2.00)	(5.77)	(5.09)	(2.48)	(7.09)	(6.55)	(3.07)
Age	0.002***	0.002***	0.000	-0.002***	-0.002***	-0.002***	0.001***	0.001***	0.000	0.002***	0.003***	0.002***
	(4.04)	(4.21)	(0.67)	(-10.27)	(-10.08)	(-10.12)	(2.88)	(3.18)	(1.60)	(8.67)	(8.80)	(5.61)
Age Squared	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***
	(-1.50)	(-1.42)	(-0.66)	(-5.19)	(-5.21)	(-4.94)	(-0.65)	(-0.57)	(-0.30)	(-4.04)	(-3.85)	(-2.75)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.128	0.138	0.207	0.125	0.166	0.177	0.080	0.140	0.151	0.082	0.129	0.162
N	10,312	10,312	9,014	10,312	10,312	9,014	10,312	10,312	9,014	10,312	10,312	9,014

Panel B

Main	Cryptocurrencies	Stocks or Mutual Funds
	(1)	(2)
Mental Accounting	0.253***	-0.114*
	(3.48)	(-1.86)
Risk Tolerance	0.274**	0.148
	(2.37)	(1.49)
Financial Knowledge	0.017	0.062
	(0.30)	(1.32)
Age	-0.035***	0.012***
	(-11.99)	(5.28)
Age Squared	-0.001***	0.000
	(-4.64)	(1.58)
Log Income	-0.121**	0.002
	(-2.21)	(0.03)
Selection Equation: Participation in Risky Markets		
Mental Accounting	-0.138***	-0.137***
	(-4.53)	(-4.50)
Particpation in Prov	3.130***	3.167***
	(7.11)	(7.28)
Risk Tolerance	0.871***	0.869***
	(21.86)	(21.83)
Financial Knowledge	0.219***	0.219***
	(10.83)	(10.81)
	(7.11)	(7.28)
College	0.435***	0.440***
	(14.17)	(14.58)
Gender	0.372***	0.367***
	(11.86)	(11.89)
Log Income	0.170***	0.169***
	(7.39)	(7.36)
Age	0.007***	0.007***
	(5.45)	(5.51)
Age Squared	-0.000**	-0.000**
	(-2.29)	(-2.32)
Athrho	0.285*	-0.538***
	(1.70)	(-3.94)
Year FE	Yes	Yes
N	10312	10312

Table 3
Conditional Hypothesis: Asset Class Selection

Panel A reports the marginal effects from logistic regressions. In Columns (1) and (2), the dependent variable is participation, an indicator that takes on the value of 1 if the individual participates in any risky market (stocks, mutual funds, crypto, bonds, real estate, or options). In Columns (3) and (4), the dependent variable is an indicator that takes on a value of 1 if the individual exclusively holds cryptocurrencies. In Columns (5) and (6), the dependent variable is an indicator that takes on a value of 1 if the individual holds both crypto and traditional assets. In Columns (7) and (8), the dependent variable is an indicator that takes on a value of 1 if the individual exclusively holds traditional assets. Columns (2), (4), (6), and (8) include loss aversion as a control variable, which is an indicator variable taking on a value of 1 if the individual indicates a score of 4 or below on tolerance for losses. All analyses include my main set of control variables and account for general risk tolerance and financial knowledge. All models use robust standard errors clustered by province and year and include year fixed effects. Panel B reports the results from a two-stage Heckprobit selection model using the same dependent variables. The selection equation estimates the likelihood of participating in risky markets. T-stats are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

Panel A

Sample:	Full Sample		Market Participants					
	Participation		Only Crypto		Crypto and Traditional		Only Traditional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mental Accounting	-0.230***	-0.237***	0.038***	0.038***	0.021**	0.021**	-0.067***	-0.067***
	(-4.17)	(-4.16)	(4.02)	(4.09)	(2.27)	(2.22)	(-3.81)	(-3.85)
Gen Risk Tolerance	0.243***	0.134***	-0.004	-0.001	0.010***	0.004	0.018***	0.009
	-22.07	(11.33)	(-1.30)	(-0.17)	(2.70)	(0.95)	(3.50)	(1.63)
Loss Averse		-1.424***		0.025*		-0.039***		-0.072***
		(-18.56)		(1.88)		(-3.01)		(-3.77)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Knowledge	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.121	0.162	0.199	0.200	0.191	0.194	0.033	0.038
N	10,312	10,312	2,385	2,385	2,385	2,385	2,385	2,385

Table 3 - Continued

Panel B			
	Only Crypto	Crypto and Traditional	Only Traditional
Main	(1)	(3)	(5)
Mental Accounting	0.244***	0.156*	-0.163***
	(2.82)	(1.76)	(-2.74)
Loss Averse	-0.049	-0.414***	0.017
	(-0.34)	(-2.70)	(0.17)
General Risk Tolerance	0.018	0.038	0.001
	(0.58)	(1.11)	(0.05)
Financial Knowledge	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Selection Equation: Participation in Risky Markets			
Mental Accounting	-0.134***	-0.134***	-0.133***
	(-4.35)	(-4.37)	(-4.33)
Loss Averse	-0.859***	-0.859***	-0.856***
	(-21.09)	(-21.08)	(-21.04)
Risk Tolerance	0.078***	0.078***	0.079***
	(8.67)	(8.67)	(8.72)
Participation in Prov	2.950***	2.977***	2.989***
	(5.87)	(5.91)	(6.00)
Financial Knowledge	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Athrho	0.366*	0.142	-0.447***
	(1.74)	(0.65)	(-3.33)
N	10,312	10,312	10,312

Table 4

Other Asset Class Participation

This table reports the marginal effects of logistic regressions of Mental Accounting on asset class participation. In Columns (1)-(2) the dependent variable is bond ownership, in Columns (3)-(4) the dependent variable is real estate ownership, and in Columns (5)-(6) the dependent variable is option ownership. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holds Bonds		Holds Real Estate		Holds Options	
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	-0.006**	-0.004*	-0.009***	-0.007**	0.001	0.001
	(-2.37)	(-1.76)	(-2.83)	(-2.06)	(1.13)	(0.95)
Main Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.003	0.045	0.004	0.055	0.005	0.076
N	12,560	12,555	12,560	12,555	12,560	12,555

Table 5

CEM Matching

Panel A reports means and standard deviations of characteristics used in matching individuals with mental accounting bias to controls. I provide the characteristics for 3,892 individuals with mental accounting bias and their 5,230 matched controls described in Section 6.1. I also report the mean difference between individuals with mental accounting bias and controls and the associated t-statistics. The statistics are weighted by the CEM weights. Panel B presents the marginal effects of logistic regression estimates of Mental Accounting and asset class participation using coarsened exact matching (CEM). Individuals are matched by Age, Income Quintile, Education, Gender, Year, Risk Tolerance, and Financial Knowledge. The dependent variable in Column (1) is participation in any risky market, an indicator that takes on the value of 1 if the individual participates in any of the following asset classes: stocks, mutual funds, cryptocurrencies, bonds, real estate, or options. The dependent variable in Column (2) is participation in cryptocurrencies, in Column (3) is participation in individual stocks, in Column (4) is participation in mutual funds, in Column (5) is participation in bonds, in Column (6) is participation in real estate, and in Column (7) is participation in options. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables Entering the Match						
Full Sample						
	(1) Individuals with Mental Accounting (N=3,892)		(2) Individuals w/o Mental Accounting (N=5,230)		(1)-(2)	
	Mean	SD	Mean	St.Dev	Mean	t-stat
Age	54.73	16.49	54.86	16.44	-0.13	(-0.32)
Income	41690.35	36055.26	41770.54	33060.41	-80.19	(-0.10)
Gender	0.48	0.50	0.48	0.50	0.00	
College	0.37	0.48	0.37	0.48	0.00	
High Risk Tolerance	0.07	0.25	0.07	0.25	0.00	
High Financial Knowledge	0.34	0.47	0.34	0.47	0.00	
Year	2021	1.43	2021	1.43	0.00	

Table 5 - Continued

Panel B

	Participation	Cryptocurrencies	Stocks	Mutual Funds	Bonds	Real Estate	Options
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mental Accounting	-0.039***	0.012***	-0.023***	-0.028***	0.004***	-0.006**	-0.011***
	(-4.54)	(3.14)	(-3.73)	(-4.09)	-2.63	(-2.12)	(-2.65)
Pseudo R-squared	0.002	0.004	0.003	0.003	0.003	0.003	0.052
N	9,122	9,122	9,122	9,122	9,122	9,122	9,122

Table 6

Instrument: Pocket Money During Childhood

This table presents the results of my instrumental variable analysis, where Mental Accounting is instrumented through an indicator that captures whether the individual received an allowance during childhood. The analysis is restricted to individuals who participate in risky assets. Column (1) presents the first-stage results, while Column (2) reports the results of the instrumental variable analysis on cryptocurrency participation, Column (3) on individual stock participation, Column (4) on mutual fund participation, Column (5) on bond participation, Column (6) on real estate participation, and Column (7) on options participation. Each table includes Cragg-Donald F-statistics to assess the strength of the instrument. All regressions incorporate year fixed effects. T-statistics are reported in parentheses. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Market Participants						
	1st Stage	2nd Stage					
Dependent Variable:	Mental Accounting	Cryptocurrencies	Stocks	Mutual Funds	Bonds	Real Estate	Options
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child Allowance	0.086***						
	(4.37)						
Mental Accounting		1.148***	-0.551**	-0.012	-0.480***	-0.481**	0.105*
		-3.91	(-2.09)	(-0.05)	(-2.71)	(-2.32)	(1.7)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,562	2,562	2,562	2,562	2,562	2,562	2,562
Cragg-Donald F-stat		18.786	18.786	18.786	18.786	18.786	18.786

Table 7

Consistency

This table reports the marginal effects of logistic regressions. The main dependent variable *Mental Accounting Consistent* is an indicator that takes on a value of 1 if the individual consistently exhibits signs of Mental Accounting throughout the entire sample period. The independent variable is an indicator variable that takes on a value of 1 if the individual held cryptocurrency at some point during the sample period. The sample is restricted to participants who appear in each year of the sample period (2019-2023). Control variables are averaged over the entire period. Table A.1 presents the definitions of all variables. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holds Crypto During Sample Period		
	(1)	(2)	(3)
Mental Accounting Consistent	0.016*	0.018**	0.016**
	(1.87)	(2.12)	(1.98)
Avg Income	0.000**	0	0
	-2.33	-0.98	-0.64
Avg Education	0.001	-0.005	-0.01
	-0.05	(-0.40)	(-0.78)
Avg Age	-0.002***	-0.001***	-0.001***
	(-4.25)	(-2.94)	(-2.87)
Avg Risk Tolerance		0.035***	0.030***
		-4.57	-4.04
Avg Financial Knowledge			0.022**
			-2.41
Pseudo R-squared	0.075	0.118	0.131
N	1,348	1,294	1,294

Table 8

Mental Accounting and Stock Selection

This table presents regression estimates of mental accounting and stock selection. Risk and return deciles are based on all stocks held by individuals in my sample. Individuals have to report 1 to 10 stock names. Since 75% of individuals hold a maximum of only three stocks, I focus my analysis on the first three stocks mentioned. The dependent variable in Column (1) estimates the log likelihood of holding stocks within the Top or Bottom Return Decile. The dependent variable in Column (2) indicates the log likelihood of holding stocks in the top two risk deciles. The dependent variable in Column (3) is the average Sharpe ratio of the three stocks. The dependent variable in Column (4) is financial literacy. Columns (1)-(2) use logit models. Columns (3)-(4) use OLS regressions. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	First 3 Stocks			
	Top or Bottom Return Decile	Highest Risk Deciles	Average Sharpe Ratio	Stock Holders: Financial Literacy
	(1)	(2)	(3)	(4)
Mental Accounting	0.546***	0.375*	-0.100***	0.104
	(3.361)	(1.683)	(-3.158)	(1.490)
Main Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.0447	0.0758	0.047	0.159
N	727	754	727	754

Table 9

Alternative Measure: Number of Checking Accounts

This table reports the regression estimates on the number of checking accounts as an alternative measure of mental accounting. In Columns (1) through (3), the dependent variable is the number of checking accounts an individual holds in his/her name (excluding joint accounts). Columns (1)-(3) use OLS. In Column (4), the dependent variable is cryptocurrency participation. Column (4) uses a logistic regression model, and coefficients are presented as marginal effects. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Number of Personal Checking Accounts			Holds Crypto
	(1)	(2)	(3)	(4)
# Personal Checking Accounts				0.006*
				(1.89)
Mental Accounting	0.084***	0.083***	0.083***	
	(5.87)	(5.82)	(5.81)	
Total $ in Checking Accounts		0.000	0.000	-0.000
		(0.65)	(0.65)	(-0.92)
Financial Knowledge			0.001	
			(0.09)	0.016***
Main Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.114	0.114	0.114	0.131
N	8,666	8,650	8,650	8,650

Table 10

Behavioral Variables: Crypto Investors versus Traditional Investors

This table reports the marginal effects of logit regression estimation results of alternative behavioral measures and cryptocurrency ownership. The outcome variable crypto versus traditional is a dummy that takes on a value of 1 if the individual invests in crypto and 0 if the individual invests in traditional assets. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto vs. Traditional Investors							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Preference for Leverage	0.03							
	(1.45)							
General Risk Tolerance		-0.002						
		(-0.29)						
High Risk Taken			0.012					
			(1.26)					
Optimism				-0.018**				
				(-2.03)				
High Locus of Control					0.021			
					-1.43			
Short Term Horizon						-0.015		
						(-0.80)		
Financial Knowledge							-0.018	
							(-1.25)	
Works in Fin or Bus								0.012
								(0.74)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk Tolerance	No	No	No	Yes	Yes	Yes	Yes	Yes
Financial Knowledge	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.202	0.200	0.203	0.214	0.213	0.213	0.212	0.212
N	1,942	1,942	1,763	1,942	1,942	1,942	1,942	1,942

Table 11

Saving Motives

This table presents the marginal effects of logistic regressions on saving motives and asset class selection. The dependent variable in columns (1) through (6)is an indicator that takes on a value of 1 if the individual exclusively holds crypto. The savings motives variables are derived from five survey questions assessing the individual's saving motives. A dummy variable is assigned a value of 1 if the individual rates its importance as 4 or above on a scale from 1 to 7. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holds Only Crypto					
	(1)	(2)	(3)	(4)	(5)	(6)
Savings Motives:						
Dividends	0.008***					
	(2.67)					
Bequest		0.009***				
		(2.97)				
Own Business			0.010***			
			(2.63)			
Unexpected expenses				-0.002		
				(-0.43)		
Future Liabilities					0.001	
					(0.22)	
Pension						-0.004
						(-1.06)
Fin Know. and Risk Tolerance	Yes	Yes	Yes	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.118	0.128	0.091	0.118	0.116	0.098
N	9,383	9,480	7,037	10,656	10,575	9,007

Appendix

A.1: Description of Variables Used in this Study

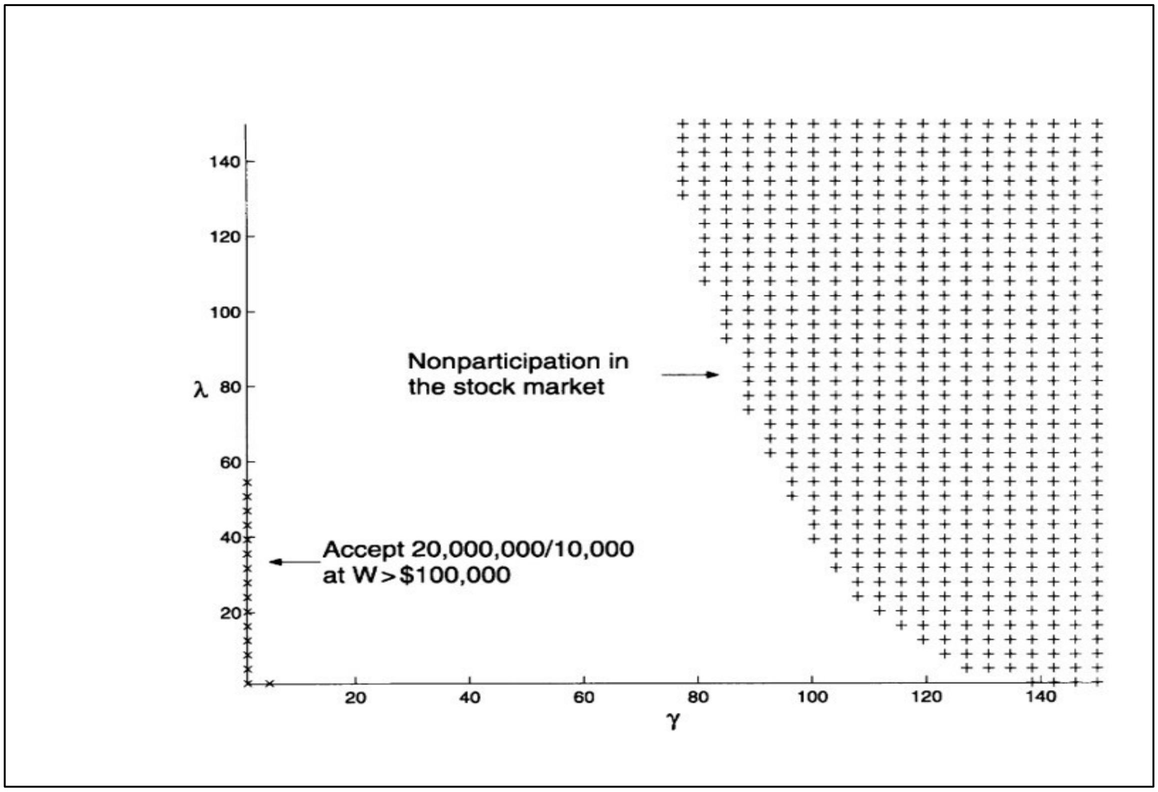
Code	**Definition**
Mental Accounting	A dummy variable that takes a value of 1 if the individual answered ”Yes” to the question: ”Do you put money aside for specific purposes (such as holidays, clothes, rent, etc.) to keep separate amounts for different purposes? This may involve, for example, depositing money into separate bank accounts or using separate envelopes or jars.”
High Risk Tolerance	A dummy variable that takes a value of 1 if the average score for the following survey questions is above 4 on a scale of 1 to 7 (where 7 means ”totally agree” and 1 means ”totally disagree”) and 0 otherwise: • ”If I want to improve my financial position, I should take financial risks.” • ”I am prepared to take the risk to lose money when there is also a chance to gain money.”
Financial Knowledge	This variable measures self-assessed financial knowledge on a scale from 1 to 4, where 1 means ”not knowledgeable” and 4 means ”very knowledgeable.”
High Risk Taken	A dummy variable that takes a value of 1 if the individual answered 4 or above to the question: ”How much risk have you taken?” on a scale from 1 to 5 (where 1 means ”I have not taken any risks at all” and 5 means ”I have often taken great risks”).
Works in Finance or Business	A dummy variable that takes a value of 1 if the individual indicated that they work in the finance or business industry.
Loss Aversion	A dummy variable that takes a value of 1 if the individual answered 4 or below to the question: ”I am prepared to take the risk of losing money when there is also a chance to gain money,” on a scale from 1 to 7 (where 1 means ”totally disagree” and 7 means ”totally agree”).
Child Allowance	A dummy variable that takes a value of 1 if, when asked whether they received a regular allowance from their parents between ages 8 and 12, the individual answered ”Yes, almost always” or ”Yes, but it was sometimes forgotten.” It equals 0 if the response was ”Occasionally” or ”No.”
Investment Choice	Ordered categorical variable representing an individual's portfolio holdings based on risk-return profile. Category 1 includes individuals holding only bonds or real estate (lowest risk, lowest return). Category 2 includes those holding stocks or mutual funds, either alone or with bonds/real estate, but without cryptocurrencies. Category 3 includes individuals holding stocks, mutual funds, assets from Category 1, and cryptocurrencies. Category 4 includes individuals holding only cryptocurrencies (highest risk, highest return).

Code	Definition
Budget Education	Measures the level of budgeting education received from (grand)parents between ages 12 and 16 on a scale from 1 to 4, where 1 means ”Yes, they gave me a lot of advice and practical help,” and 4 means ”No.”
Saving Education	Measures whether (grand)parents encouraged the individual to save money between ages 12 and 16, on a scale from 1 to 4, where 1 means ”Yes, they emphasized the necessity of saving,” and 4 means ”No, not at all.”
General Risk Tolerance	A scale variable from 1 to 7 based on the response to the statement: ”If I want to improve my financial position, I should take financial risks,” where 1 means ”totally disagree” and 7 means ”totally agree.”
Short Time Horizon	A dummy variable that takes the value of 1 if the individual indicated that their household’s most important planning period for expenditures and savings is ”the next couple of months” or ”the next year,” in response to the question about the time frame for income planning.
High Locus of Control	A dummy variable that takes a value of 1 if the individual responded with a score above 4 to the statement: ”Whether or not I get to become wealthy depends mostly on my ability,” on a scale from 1 to 7 (where 1 means ”totally disagree” and 7 means ”totally agree”).
Saving Motives	A dummy variable that takes a value of 1 if the individual indicates a score of 4 and above when ranking the importance of the following saving motives on a scale of 1 to 7 (robustness checks were done with a threshold of 5): • Future Liabilities • Unexpected Expenses • Bequest • Dividends • Own Business • Pension
Numeracy	This variable is measured as the average score on four probability math exercises, with each correct answer contributing 1 point to the score.
Google Search	This variable represents the Google search volume for ”bitcoin” by province, aggregated from 2018 to 2022.

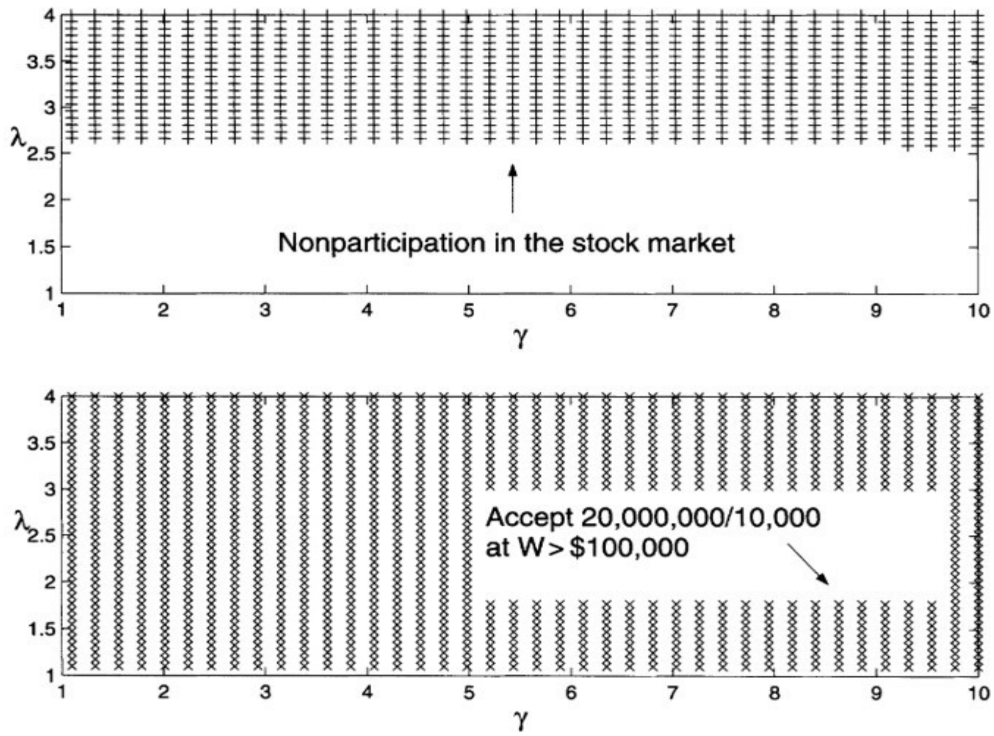
A.2 Original Simulation Results from Barberis, Huang and Thaler (2006)

This Figure displays original simulation results from Barberis, Huang, and Thaler (2006). Panel A illustrates, non-stock market participation and acceptance of 20,000,000/10,000 without narrow framing. Panel B displays the simulation results with narrow framing: the top area shows non-stock market participation, and below it demonstrates acceptance of 20,000,000/10,000 with narrow framing. The parameter γ describes sensitivity to losses and λ describes risk aversion

Panel A: Without Narrow Framing



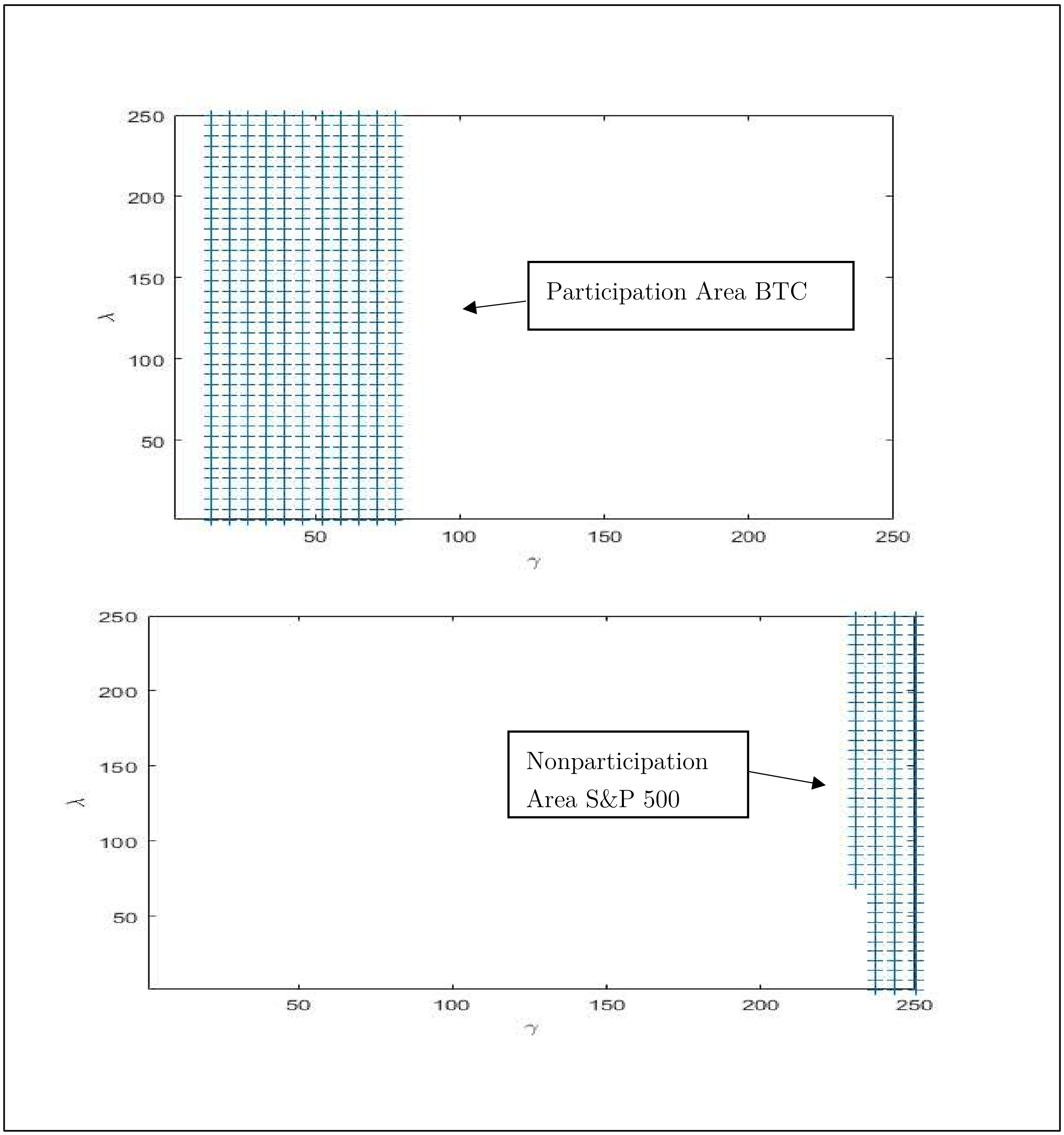
Panel B: With Narrow Framing



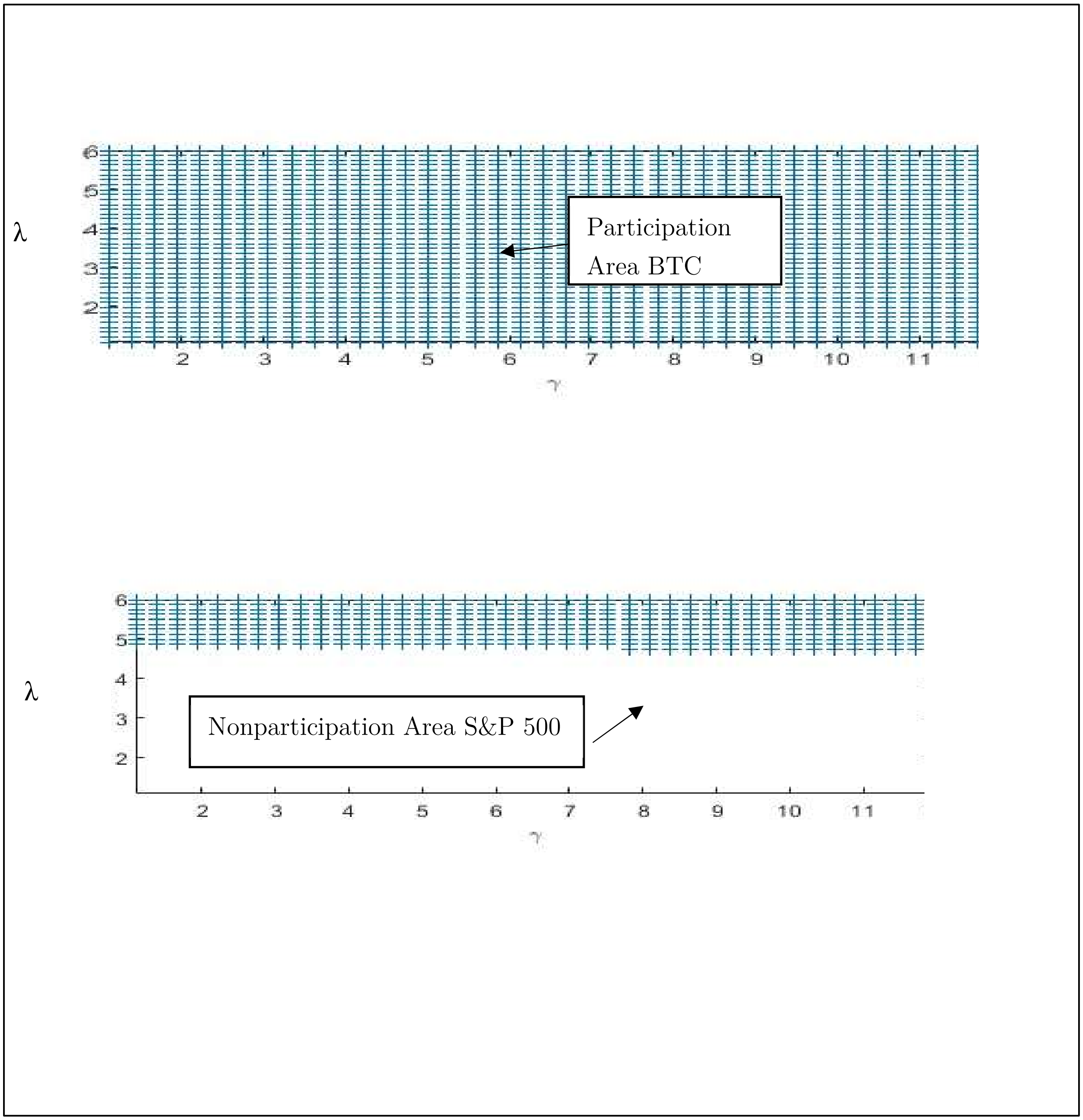
A.3 Simulation Results BTC and S&P 500

This Figure displays simulation results using statistical properties of BTC and statistical properties of S&P 500. Panel A illustrates, non-stock market participation and participation in BTC without mental accounting. Panel B displays the simulation results with narrow framing: the top area shows non-stock market participation, and below is participation in BTC with mental accounting. The parameter γ describes sensitivity to losses and λ describes risk aversion. BTC and S&P 500 statistical properties are based on annual returns and standard deviations from 2014-2022

Panel A: Without Mental Accounting

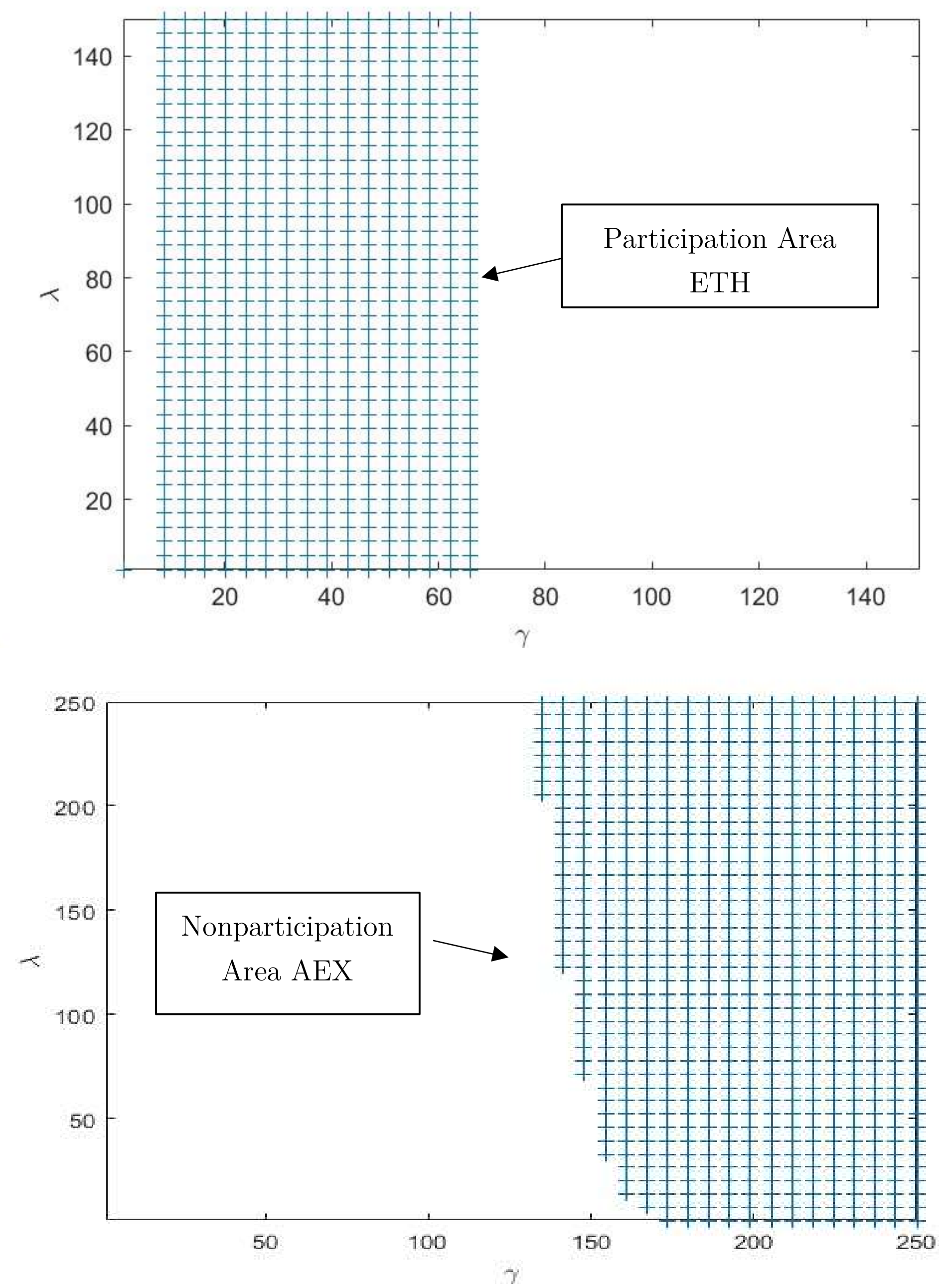


Panel B: With Mental Accounting

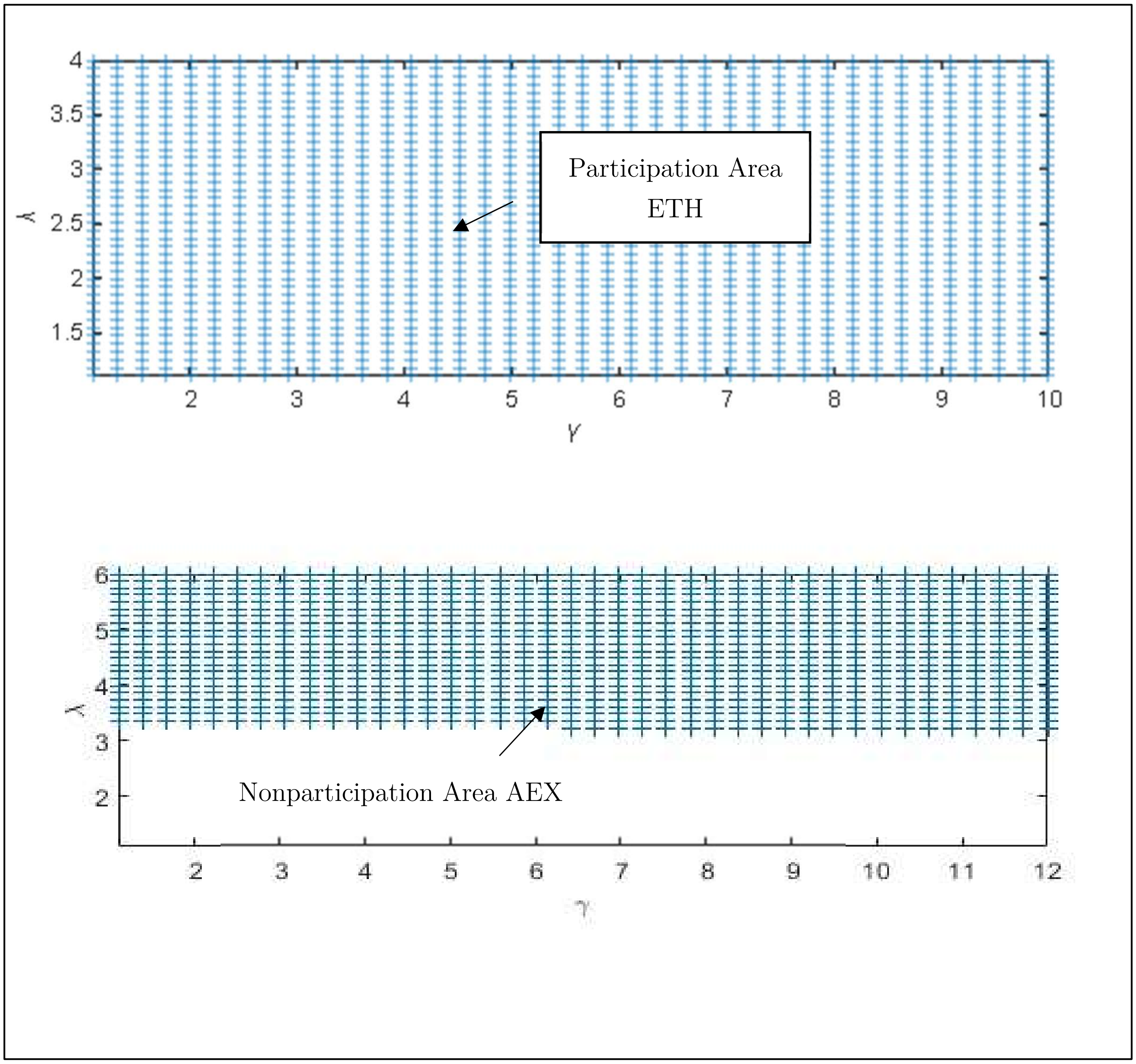


A.4 Simulation Results ETH and AEX

This Figure displays simulation results using properties of ETH and statistical properties of AEX. Panel A illustrates, non-stock market participation and participation in ETH without mental accounting. Panel B displays the simulation results with narrow framing: the top area shows non-stock market participation, and below is participation in ETH with mental accounting. The parameter γ describes sensitivity to losses and λ describes risk aversion. ETH and AEX statistical properties are based on annual returns and standard deviations from 2014-2022

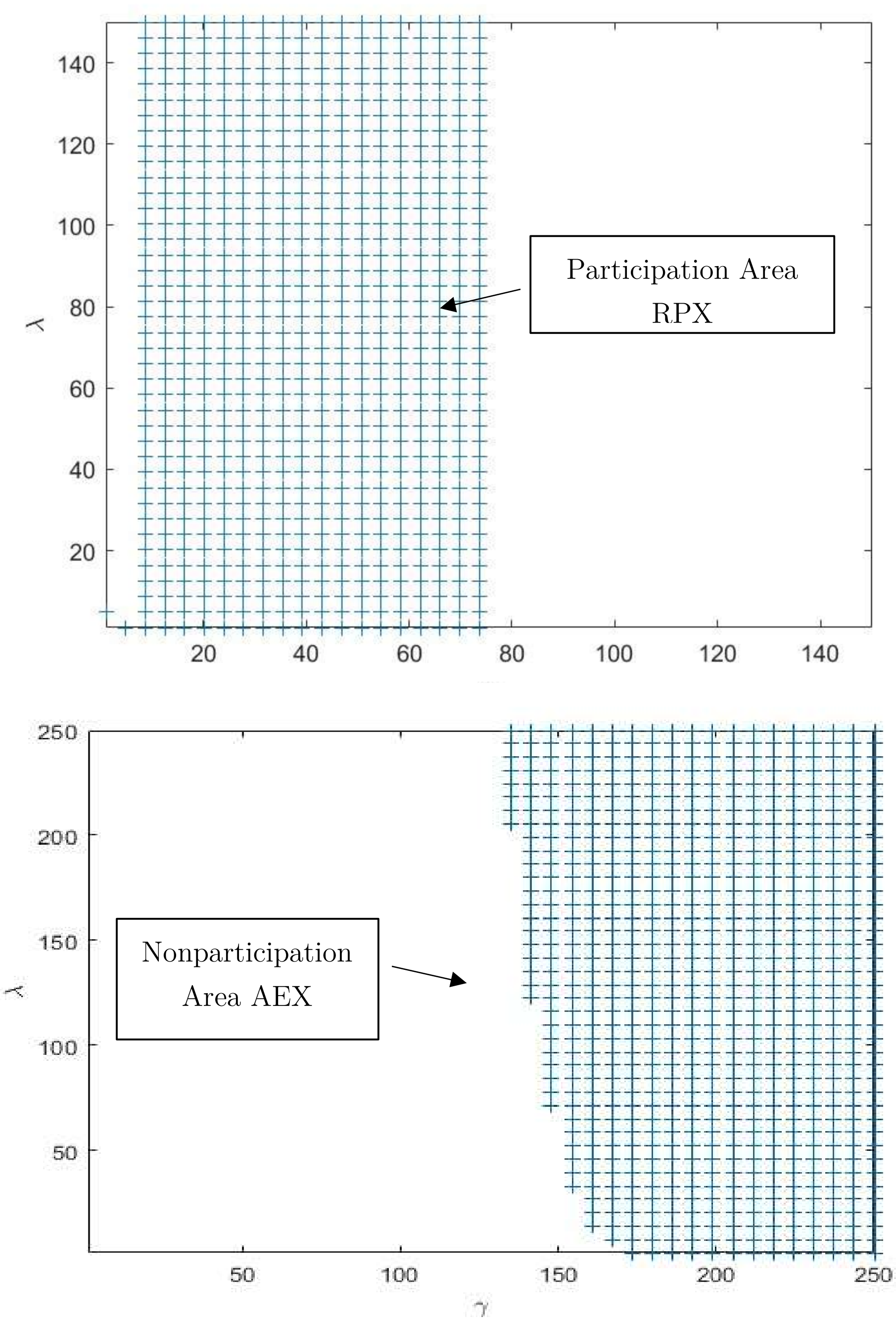


Panel B: With Mental Accounting

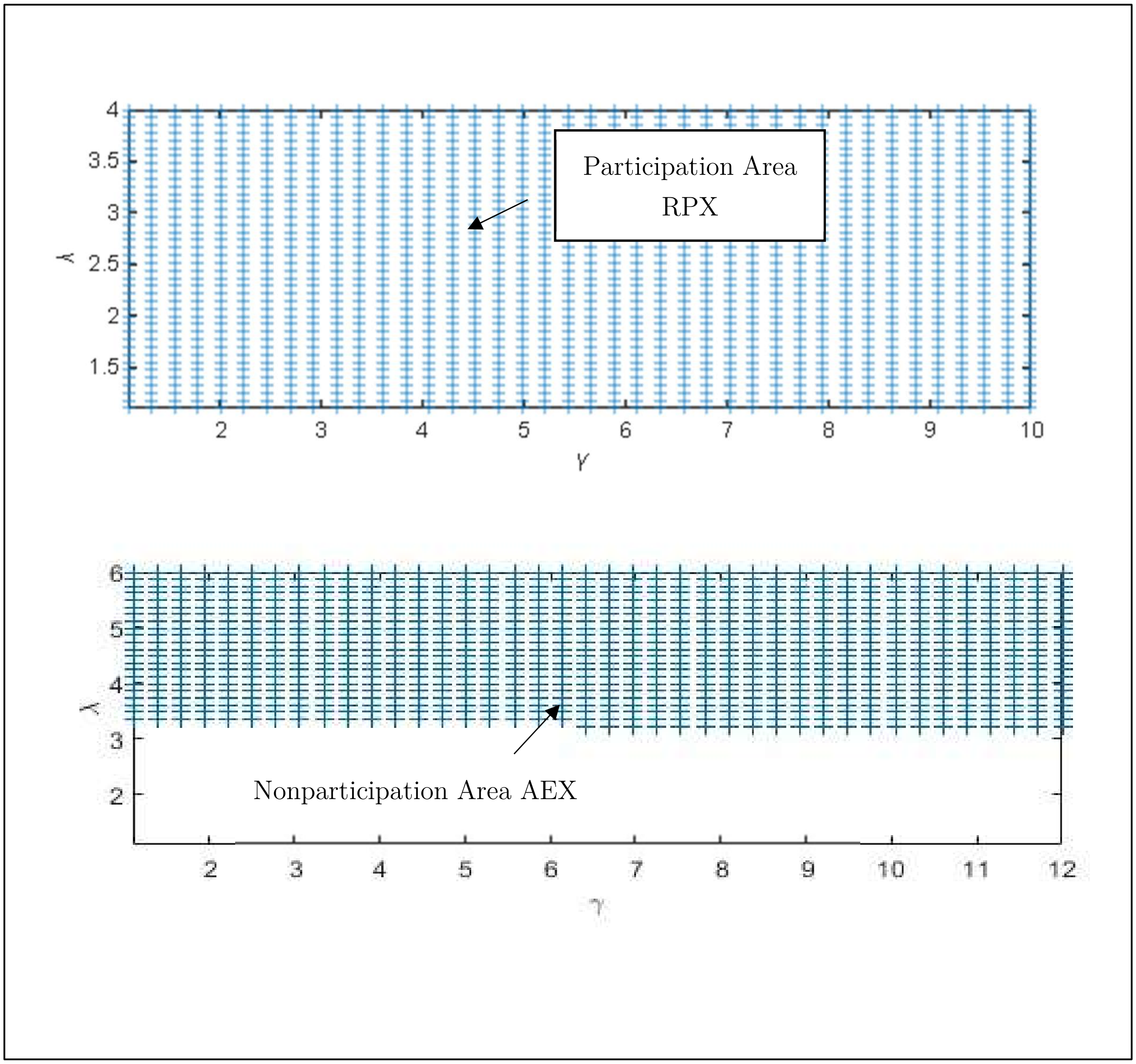


A.5 Simulation Results RPX and AEX

This Figure displays simulation results using properties of RPX and statistical properties of AEX. Panel A illustrates, non-stock market participation and participation in RPX without mental accounting. Panel B displays the simulation results with narrow framing: the top area shows non-stock market participation, and below is participation in RPX with mental accounting. The parameter γ describes sensitivity to losses and λ describes risk aversion. RPX and AEX statistical properties are based on annual returns and standard deviations from 2014-2022

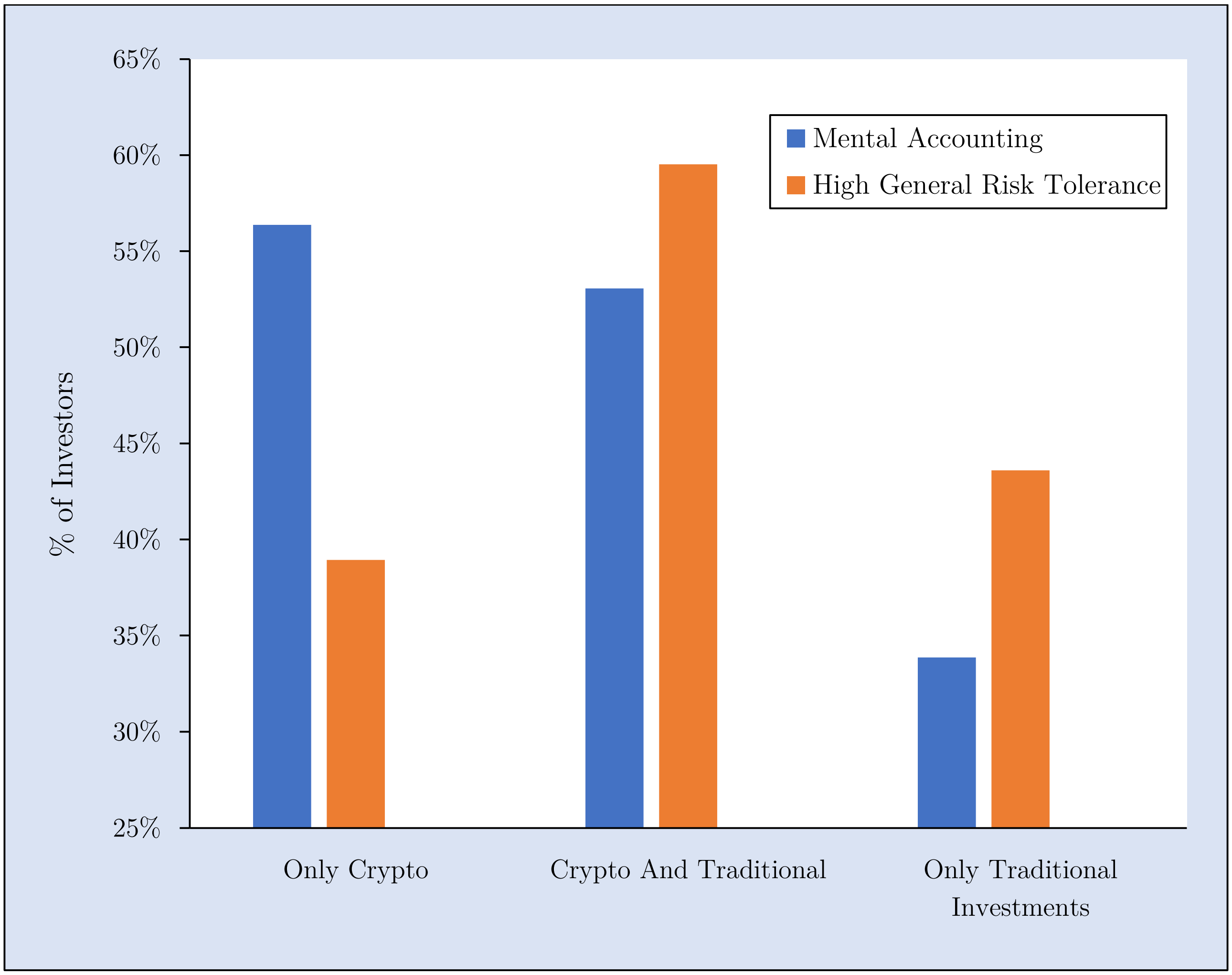


Panel B: With Mental Accounting



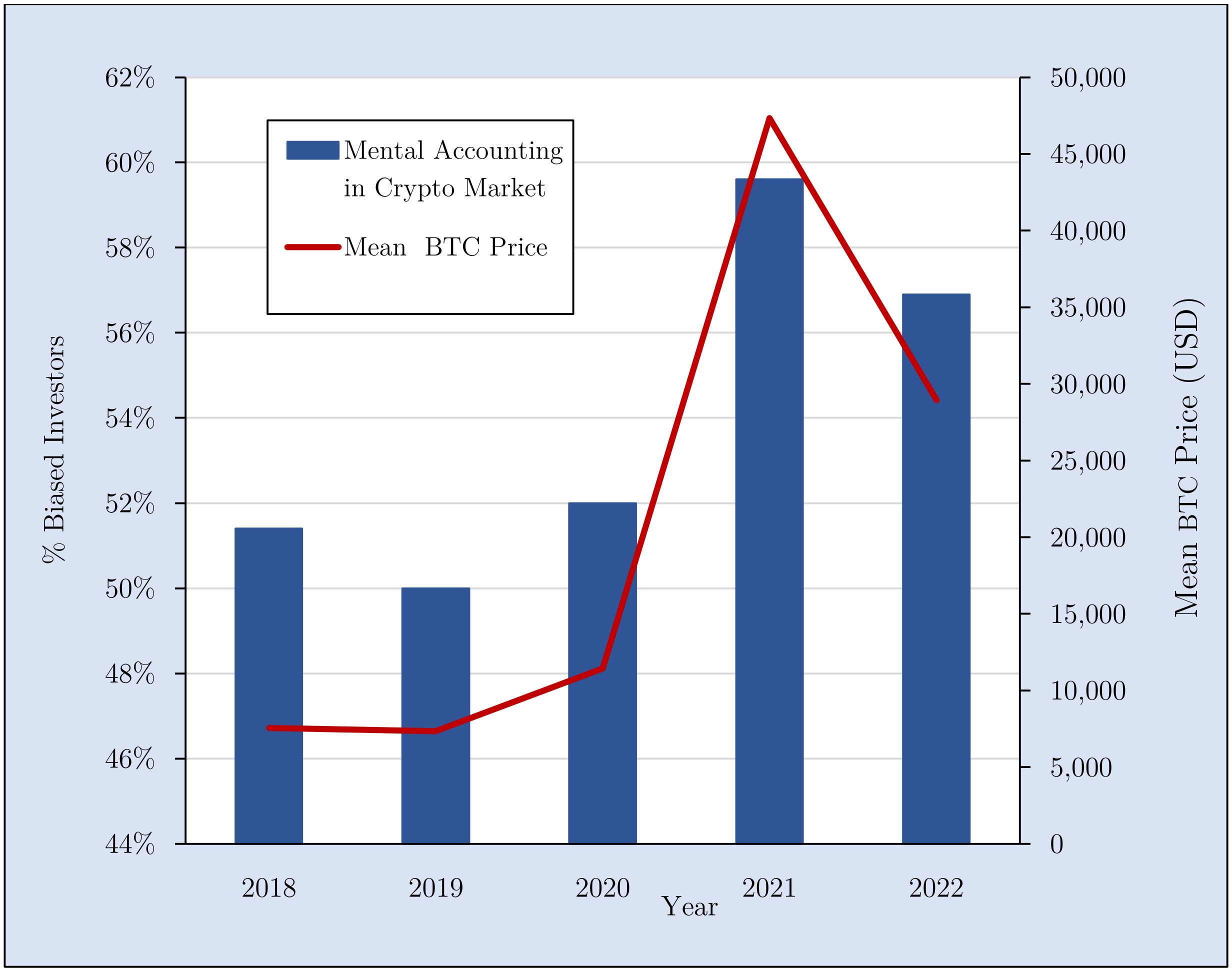
A.6 High-Risk Tolerance and Mental Accounting Bias by Investor Group

This figure displays the proportions of investors with high-risk tolerance and mental accounting bias across different investor groups: those who invest exclusively in cryptocurrencies, those who invest in both cryptocurrencies and traditional assets, and those who invest only in traditional assets.



A.7 Proportion of Biased Investors in the Crypto Market and BTC Price

This figure illustrates the yearly proportion of investors in the crypto market exhibiting mental accounting bias from 2018 to 2022, represented by bars. Overlaid is the average annual BTC price, depicted as a line.



A.8 Asset Class Selection: Baseline Controls

This table shows the estimates of the logit regression of cryptocurrency ownership and stock ownership and basic controls. Two control groups were utilized: Column (1) focuses on crypto participation, and Column (2) studies participation decisions in traditional markets. Table A.1 presents the definitions of all variables. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Cryptocurrency Participation	Stock Market Participation
	(1)	(2)
Age	-0.056***	0.014***
	(-11.51)	(5.00)
Age Squared	-0.002***	0.000
	(4.93)	(0.25)
College	0.064	0.737***
	(0.48)	(10.38)
Log Income	-0.034	0.273***
	(0.49)	(5.70)
General Risk Tolerance	0.289***	0.327***
	(8.11)	(19.15)
Financial Knowledge	0.388***	0.514***
	(6.43)	(11.74)
Pseudo R-squared	0.138	0.107
N	10,312	10,312

A.9 Mental Accounting and Extended Controls

This table presents the log-odds estimates of logistic regressions on Mental Accounting and Asset Class Participation. The dependent variable in Panel A is cryptocurrency ownership. The dependent variable in Panel B is individual stock ownership, and the dependent variable in Panel C is mutual fund ownership. Table A.1 presents the definitions of all variables. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A	Crypto				
	(1)	(2)	(3)	(4)	(5)
Mental Accounting	0.316***	0.292***	0.293***	0.327***	0.242**
	(4.02)	(3.52)	(3.49)	(3.61)	(2.19)
Risk Tolerance		1.137***	1.071***	1.109***	1.184***
		(8.95)	(8.39)	(7.90)	(8.63)
Financial Literacy			0.274***	0.267***	0.220***
			(4.41)	(3.67)	(2.58)
Log Wealth				0.096**	0.095*
				(2.19)	(1.87)
Optimism					0.039
					(0.47)
Number of Children					0.044
					(0.79)
Married					0.027
					(0.19)
Urbanization					0.021
					(0.32)
College	0.287***	0.150	0.090	-0.062	-0.138
	(2.96)	(1.19)	(0.71)	(-0.40)	(-0.79)
Gender	1.184***	0.951***	0.901***	0.860***	0.853***
	(10.41)	(9.02)	(8.61)	(7.43)	(7.07)
Log Income	0.029	-0.054	-0.083	-0.163**	-0.191**
	(0.56)	(-0.77)	(-1.18)	(-1.99)	(-2.00)
Age	-0.059***	-0.058***	-0.057***	-0.062***	-0.062***
	(-12.60)	(-11.55)	(-11.40)	(-10.69)	(-9.89)
Age Squared	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***
	(-7.55)	(-5.39)	(-5.39)	(-5.06)	(-3.63)
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.125	0.162	0.166	0.177	0.179
N	12,555	10,312	10,312	9,057	7,727

A.9. - Continued

Panel B	Individual Stocks				
	(1)	(2)	(3)	(4)	(5)
Mental Accounting	-0.269***	-0.289***	-0.291***	-0.243***	-0.273***
	(-3.73)	(-3.62)	(-3.61)	(-2.80)	(-3.15)
Risk Tolerance		1.513***	1.439***	1.382***	1.458***
		(15.11)	(13.90)	(12.76)	(11.82)
Financial Literacy			0.380***	0.299***	0.270***
			(7.83)	(6.00)	(4.98)
Log Wealth				0.251***	0.242***
				(10.43)	(9.95)
Optimism					0.015
					(0.25)
Number of Children					-0.217***
					(-3.49)
Married					-0.406***
					(-4.58)
Urbanization					-0.027
					(-0.70)
College	0.850***	0.766***	0.696***	0.536***	0.560***
	(14.03)	(10.34)	(9.81)	(7.84)	(10.65)
Gender	1.067***	0.886***	0.801***	0.642***	0.684***
	(17.53)	(11.82)	(10.92)	(8.61)	(7.90)
Log Income	0.389***	0.290***	0.249***	0.132**	0.250***
	(8.10)	(5.77)	(5.08)	(2.48)	(3.76)
Age	0.004*	0.010***	0.011***	0.005	0.008**
	(1.68)	(2.86)	(3.15)	(1.55)	(2.32)
Age Squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.54)	(-0.65)	(-0.57)	(-0.28)	(-1.39)
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.080	0.130	0.140	0.151	0.161
N	12,555	7,727	10,312	9,057	7,727

A.9. - Continued

Panel B	Individual Stocks				
	(1)	(2)	(3)	(4)	(5)
Mental Accounting	-0.269***	-0.289***	-0.291***	-0.243***	-0.273***
	(-3.73)	(-3.62)	(-3.61)	(-2.80)	(-3.15)
Risk Tolerance		1.513***	1.439***	1.382***	1.458***
		(15.11)	(13.90)	(12.76)	(11.82)
Financial Literacy			0.380***	0.299***	0.270***
			(7.83)	(6.00)	(4.98)
Log Wealth				0.251***	0.242***
				(10.43)	(9.95)
Optimism					0.015
					(0.25)
Number of Children					-0.217***
					(-3.49)
Married					-0.406***
					(-4.58)
Urbanization					-0.027
					(-0.70)
College	0.850***	0.766***	0.696***	0.536***	0.560***
	(14.03)	(10.34)	(9.81)	(7.84)	(10.65)
Gender	1.067***	0.886***	0.801***	0.642***	0.684***
	(17.53)	(11.82)	(10.92)	(8.61)	(7.90)
Log Income	0.389***	0.290***	0.249***	0.132**	0.250***
	(8.10)	(5.77)	(5.08)	(2.48)	(3.76)
Age	0.004*	0.010***	0.011***	0.005	0.008**
	(1.68)	(2.86)	(3.15)	(1.55)	(2.32)
Age Squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.54)	(-0.65)	(-0.57)	(-0.28)	(-1.39)
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.080	0.130	0.140	0.151	0.161
N	12,555	7,727	10,312	9,057	7,727

A.10 Mental Accounting and Loss Aversion

This table reports the marginal effects of logistic regressions of Loss Aversion on Mental Accounting. In all Columns the dependent variable is Mental Accoutning, Column (1) includes my main set of controls, while Column (2) also accounts for Risk Tolerance and Column (3) additionally accounts for Financial Knowledge. Table A.1 presents the definitions of all variables. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Mental Accounting		
	(1)	(2)	(3)
Loss Averse	0.011	0.008	0.013
	(0.95)	(0.69)	(1.17)
Risk Tolerance		-0.002	-0.002
		(-0.56)	(-0.57)
Financial Knowledge			0.017**
			(2.52)
College	-0.009	-0.009	-0.011
	(-1.11)	(-1.07)	(-1.34)
Gender	-0.036***	-0.035***	-0.038***
	(-3.97)	(-3.86)	(-4.11)
Log Income	0.037***	0.037***	0.035***
	(5.50)	(5.57)	(5.25)
Age	-0.005***	-0.005***	-0.005***
	(-12.91)	(-12.99)	(-12.66)
Age Squared	0.000	0.000	0.000
	(0.74)	(0.72)	(0.73)
Pseudo R-Squared	0.026	0.026	0.026
N	10,312	10,312	10,312

A.11 Ordered Logit: Investment Choice

This table presents the results of the ordered logit regression, where the dependent variable, Investment Choice, is an ordered categorical variable representing an individual's portfolio holdings based on their risk-return profile. Category 1 includes individuals who hold only bonds or real estate, representing the lowest-risk, lowest-return investments. Category 2 consists of individuals who hold stocks or mutual funds, either alone or in combination with bonds and real estate, but without cryptocurrencies. Category 3 includes individuals who hold stocks, mutual funds, and any assets from Category 1, as well as cryptocurrencies. Category 4 consists of individuals who hold only cryptocurrencies, representing the highest-risk, highest-return portfolio. Column 1 reports the results of the main ordered logit regression. Columns (2)–(5) present the marginal effects of mental accounting for each transition between investment categories. All models include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Investment Choice	ME Step-1	ME Step-2	ME Step-3	ME Step-4
	(1)	(2)	(3)	(4)	(5)
Mental Accounting = 1	0.236***	-0.022***	-0.007**	0.011***	0.018***
	(3.36)	(-3.53)	(-2.35)	(3.26)	(3.20)
Risk Tolerance	0.407***				
	(4.36)				
Financial Knowledge	0.059				
	(0.90)				
College	-0.097				
	(-0.92)				
Gender	0.290***				
	(2.93)				
Log Income	-0.196**				
	(-2.34)				
Age	-0.043***				
	(-10.02)				
Age Squared	0.000				
	(1.51)				
Year FE	Yes				
Pseudo R-Squared	0.062				
N	2,376				

A.12 CEM Matching: Market Participants

This table presents the marginal effects of logistic regression estimates of Mental Accounting and asset class participation using coarsened exact matching (CEM) on the sample restricted to risky market participants. Individuals are matched by Age Group, Income Quintile, Education, Gender, Year, Risk Tolerance, and Financial Knowledge. The dependent variable in Column (1) is participation in any risky market, an indicator that takes on the value of 1 if the individual participates in any of the following asset classes: stocks, mutual funds, cryptocurrencies, bonds, real estate, or options. The dependent variable in Column (2) is participation in cryptocurrencies, in Column (3) is participation in individual stocks, in Column (4) is participation in mutual funds, in Column (5) is participation in bonds, in Column (6) is participation in real estate, and in Column (7) is participation in options. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto	Stocks	Mutual Funds	Bonds	Real Estate	Options
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	0.062***	-0.038*	-0.040*	-0.021*	-0.011	0.017***
	-3.95	(-1.79)	(-1.90)	(-1.66)	(-0.70)	-2.87
Pseudo R-squared	0.0072	0.001	0.0011	0.0317	0.002	0.0002
N	2,316	2,316	2,316	2,316	2,316	2,316

A.13 Behavioral Variables: Crypto Investors Versus Full Sample

This table reports the log-odds coefficient of logit regression estimation results of alternative behavioral measures and cryptocurrency ownership. The dependent variable is Crypto. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holds Crypto							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Preference for Leverage	0.058							
	(1.57)							
General Risk Tolerance		0.236***						
		(5.81)						
High Risk Taken			0.786***					
			(3.54)					
Optimism				0.03				
				(0.41)				
High Locus of Control					0.308**			
					(2.52)			
Short Term Horizon						-0.184		
						(-1.32)		
Financial Knowledge							0.238***	
							(3.00)	
Works in Fin or Bus								0.312**
								(2.32)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk Tolerance	No	No	No	Yes	Yes	Yes	Yes	Yes
Financial Knowledge	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.138	0.153	0.184	0.170	0.172	0.171	0.170	0.167
N	9,733	9,733	4,740	9,733	9,733	9,733	9,733	9,733

A.14 Robustness: Numeracy Score

This table presents the logit estimation results of the main analysis with the inclusion of numeracy as a control variable. In Columns (1) and (4), the dependent variable is cryptocurrency participation. In Columns (2) and (5), the dependent variable is Individual Stock Ownership, and in Columns (3) and (6), the dependent variable is Mutual Fund participation. Numeracy is measured as the average score on four probability math exercises, with each correct answer contributing 1 point. Columns (1) through (3) include the main set of controls, while Columns (4) through (6) additionally control for risk tolerance and financial knowledge. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto	Stocks	Mutual Funds	Crypto	Stocks	Mutual Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	0.330***	-0.228***	-0.204***	0.308***	-0.271***	-0.221***
	(3.67)	(-3.06)	(-3.30)	(3.18)	(-3.06)	(-3.25)
Numeracy Score	0.763***	1.052***	1.059***	0.364*	0.638***	0.730***
	(3.61)	(7.60)	(7.28)	(1.86)	(4.30)	(4.69)
Risk Tolerance				1.204***	1.421***	1.265***
				(9.81)	(11.79)	(16.66)
Financial Knowledge				0.237***	0.418***	0.355***
				(3.67)	(7.86)	(8.32)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.131	0.086	0.092	0.177	0.144	0.132
N	9,998	9,998	9,998	8,199	8,199	8,199

A.15 Robustness: Financial Education from Parents

This table presents the logit estimation results of the main analysis with the inclusion of financial education provided by parents when the individual was a child as a control variable. In Columns (1) and (4), the dependent variable is cryptocurrency participation. In Columns (2) and (5), the dependent variable is individual stock ownership. In Columns (3) and (6), the dependent variable is mutual fund participation. Financial education is measured through Budget Education Parents, which indicates education focused on budgeting, and Saving Education Parents, which indicates education focused on saving. Columns (1) through (3) include the main set of controls, while Columns (4) through (6) additionally control for risk tolerance and financial knowledge. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto	Stocks	Mutual Funds	Crypto	Stocks	Mutual Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	0.272***	-0.293***	-0.262***	0.262***	-0.300***	-0.276***
	(3.37)	(-3.99)	(-4.81)	(2.84)	(-3.70)	(-4.60)
Budget Education Parents	0.192**	-0.123**	0.057	0.148	-0.166***	0.027
	(2.38)	(-2.02)	(1.11)	(1.49)	(-2.95)	(0.54)
Saving Education Parents	-0.164	0.369***	0.427***	-0.234*	0.297***	0.424***
	(-1.34)	(5.47)	(7.39)	(-1.92)	(4.48)	(6.71)
Risk Tolerance				1.105***	1.482***	1.311***
				(8.63)	(13.88)	(20.92)
Financial Knowledge				0.252***	0.359***	0.351***
				(3.73)	(7.33)	(9.02)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.125	0.083	0.090	0.166	0.143	0.136
N	12,164	12,164	12,164	9,997	9,997	9,997

A.16 Robustness: Clustered by Household

This table presents the estimation results of the main analysis while clustering standard errors by household. Cryptocurreny Ownership is the dependent variable in Columns (1) and (4). Individual Stock Ownership is the dependent variable in Columns (2) and (3), and Mutual Fund Ownership is the dependent variable in Columns (3) and (6). Columns (1) through (3) include my main set of controls, while Columns (4) through (6) additionally control for risk tolerance and financial knowledge. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto	Stocks	Mutual Funds	Crypto	Stocks	Mutual Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	0.311**	-0.268**	-0.254***	0.293*	-0.291***	-0.267**
	(2.14)	(-2.52)	(-2.58)	(1.83)	(-2.60)	(-2.50)
Risk Tolerance				1.078***	1.439***	1.292***
				(6.34)	(12.49)	(12.53)
Financial Knowledge				0.277***	0.381***	0.369***
				(2.78)	(5.07)	(5.61)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.126	0.080	0.083	0.167	0.140	0.129
N	12,555	12,555	12,555	10,312	10,312	10,312

A.17 Robustness: Attention

This table presents the logit estimation results of the main analysis with the inclusion of Attention as a control variable. Cryptocurrency Ownership is the dependent variable in Columns (1) and (4). Individual Stock Ownership is the dependent variable in Columns (2) and (3), and Mutual Fund Ownership is the dependent variable in Columns (3) and (6). Columns (1) through (3) include my main set of controls, while Columns (4) through (6) additionally control for risk tolerance and financial knowledge. Attention is measured through the Google Search Volume for Bitcoin of each province. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crypto	Stocks	Mutual Funds	Crypto	Stocks	Mutual Funds
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Accounting	0.293***	-0.328***	-0.280***	0.277***	-0.350***	-0.288***
	(3.47)	(4.80)	(4.86)	(3.08)	(4.41)	(4.50)
Google Search	0.003	0.013***	0.013***	-0.008	0.010**	0.015***
	(0.35)	(3.48)	(3.29)	(0.92)	(2.08)	(3.22)
				1.133***	1.461***	1.294***
High Risk Tolerance				(8.98)	(13.07)	(19.29)
				0.235***	0.387***	0.370***
Financial Knowledge				(3.85)	(7.37)	(9.32)
Pseudo R-squared	0.124	0.078	0.079	0.167	0.140	0.125
N	11,283	11,283	11,283	9,343	9,343	9,343

A.18 Saving Motives: Holds Crypto

This table presents the marginal effects of logistic regressions on saving motives and asset class selection. In Columns (1) through (6) the dependent variable is crypto participation. The savings motives variables are derived from five survey questions assessing the individual's saving motives. A dummy variable is assigned a value of 1 if the individual rates its importance as 4 or above on a scale from 1 to 7. Table A.1 presents the definitions of all variables. My controls include the main control variables used in previous models. All models use robust standard errors clustered by province and year and include year fixed effects. T-stats are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holds Crypto					
	(1)	(2)	(3)	(4)	(5)	(6)
Savings Motives:						
Dividends	0.019***					
	(4.40)					
Bequest		0.016***				
		(4.08)				
Own Business			0.008			
			(1.47)			
Unexpected expenses				-0.010		
				(-1.37)		
Future Liabilities					-0.013	
					(-1.62)	
Pension						-0.007
						(-1.04)
Fin Know. and Risk Tolerance	Yes	Yes	Yes	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.168	0.166	0.133	0.162	0.161	0.139
N	8,813	8,894	8,894	10,001	9,922	8,420