Who's in? Household-targeted Government Policies and the Role of Financial Literacy in Market Participation

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Abstract

This paper evaluates the impact of household-targeted government policies on financial market participation in relation to financial literacy, focusing on potential Central Bank Digital Currency (CBDC) participation. Due to the lack of empirical data on CBDC, I use the introduction of retail Treasury Bonds in Italy as a proxy to investigate how financial literacy affects households' likelihood to engage with the new instrument. Using data from the Bank of Italy's Survey on Household Income and Wealth, I explore how financial literacy influenced households' participation in the Treasury Bond market following the 2012 introduction of retail Treasury Bonds. Results show that financial literacy positively influenced participation, although the effect is non-monotone across literacy levels, with low-financial literacy households more likely to participate than financially illiterate and high-literate households. Based on the empirical findings, I develop a theoretical model to explore how CBDC demand differs by financial literacy. The model shows that low-financial literacy households allocate more to CBDC due to limited access to diversified assets, while high-financial literacy households use risky assets to hedge against income uncertainty. These findings highlight financial literacy's role in shaping portfolio choices and CBDC adoption.

JEL codes: E42, E58, G11, G18, G53

Keywords: Central Bank Digital Currency, Financial literacy, Government policies, Market participation, Treasury Bonds

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1 Introduction

Limited participation of households in financial markets has been well-documented in the literature, resulting in potential welfare costs due to non-participation [Calvet, Campbell, and Sodini (2009), Vissing-Jorgensen (2004)]. Government policies targeted at households have the potential to increase market participation. A particularly relevant policy instrument that central banks worldwide are considering is the issuance of public money in digital form, known as Central Bank Digital Currency (CBDC). CBDCs would likely be accessible to the general public (i.e., retail), allowing everyone to have a digital wallet at a financial institution. While most research on CBDCs focuses on their implications for the banking system and financial stability [see, e.g., Assenmacher et al. (2021), Burlon, Muñoz, and Smets (2024), Chen and Filippin (2024), Chiu et al. (2023), Whited, Wu, and Xiao (2023), Williamson (2022)], there is little evidence of the effects of introducing CBDC on market participation (i.e., on the demand for a CBDC). Although everyone could access CBDC, the extent to which households use it might differ based on personal characteristics and preferences. While CBDC would be a digital form of cash and relatively easy to use, adoption may depend on individuals' understanding of its benefits and functionality, which is closely tied to their level of financial literacy.

This paper evaluates the effects of financial literacy on CBDC market participation. Given the lack of available empirical data on CBDC adoption, I use a proxy to explore how financial literacy affects the household's likelihood of engaging with the new instrument. The proxy is the introduction of retail Treasury Bonds in Italy. Both instruments are claims on the government, and they are aimed at households, making retail Treasury Bonds a suitable comparative instrument for a CBDC. Based on the empirical findings, I then develop a theoretical model to explore how CBDC demand differs by household financial literacy.

The first part of the paper uses data from the Bank of Italy's Survey on Household Income and Wealth (SHIW) to assess the impact of introducing Italian government bonds tailored to household investors on financial market participation. Italy presents an interesting case, as it has one of the lowest levels of financial literacy among OECD countries [OECD (2020)], while also showing one of the highest amounts of households' direct holdings of government debt among euro area countries [Pavot and Valenta (2021)]. These facts make Italy a particularly relevant setting for studying Treasury Bond market participation when considering financial literacy.

In 2012, the Italian government introduced retail Treasury Bonds, a subcategory of Treasury Bonds exclusively issued to retail investors (i.e., households) through a dedicated section of the Milan Stock Exchange. These bonds can be purchased through a home banking system with an online trading feature, allowing households to buy bonds without visiting a bank.[1] This direct purchase mechanism likely requires some degree of financial literacy, which is accounted for in the analysis.

Specifically, the empirical exercise addresses several key questions: (i) Did financial literacy influence households' participation in the Treasury Bond market following the introduction of retail Treasury Bonds? (ii) How did the effect vary across financial literacy levels? And (iii) Did households reallocate their portfolios after the introduction of retail Treasury Bonds? Importantly, the focus is on the extensive margin of participation (i.e., who started to hold Treasury Bonds) rather than the intensive one (i.e., how much Treasury Bonds are held).[2]

The empirical results reveal that financial literacy positively influenced participation in the Treasury Bond market after the introduction of retail Treasury Bonds. Furthermore, the effect is non-monotone across literacy levels, with households in the low-financial literate group being more likely to participate following the introduction of the new instrument compared to the financially illiterate and high-financial literate household groups. The findings also suggest a reallocation of portfolios, with households shifting investments from other government securities and stocks toward Treasury Bonds.

The second part of the paper explores how households' financial literacy affects CBDC market participation. Since the CBDC market is not yet established, I focus on the demand for CBDC. I use the empirical insights to inform the theoretical framework, which considers a two-period endowment economy with two types of households, differentiated by their financial literacy: high-financial literate and low-financial literate. The high-financial literate household can invest in risky assets and risk-free deposits, while the low-financial literate household can invest only in deposits. The government introduces a CBDC accessible to both types of households, potentially interest-bearing, and offering liquidity benefits.

The model examines how high- and low-financial literate agents allocate their portfolios in different economic environments. In the deterministic income scenario, the results reveal that low-financial literacy households hold more CBDC in absolute terms than high-financial literacy households, who rely on risky assets to hedge against income fluctuations, thereby reducing their need for CBDC. Introducing a stochastic second-period income amplifies these differences: as uncertainty rises, high-financial literacy households reallocate away from risky assets toward safer options like CBDC, while low-financial literacy households continue to depend heavily on deposits and CBDC due to limited investment options. This analysis provides policymakers with valuable insights for designing an effective CBDC that can achieve

[1] Additionally, buyers during the placement period are guaranteed to receive the quantity they request.

[2] The Italian government introduced retail Treasury Bonds to boost domestic debt holdings. This study focuses on the potential implications for household participation in the Treasury Bond market.

broad adoption across households with different financial literacy levels.

Related literature. This paper contributes to the diverse literature on financial literacy and market participation, encompassing studies from various countries. Arrondel et al. (2016) investigate the relationship between financial literacy and financial behavior in the French population using the 2011 PATER household survey and find that financial literacy significantly impacts the probability of holding stocks. Similarly, using the 2005 De Nederlandesche Bank's Household Survey, van Rooij, Lusardi, and Alessie (2011) highlight financial literacy as a key determinant of stock market participation. In recent work, Chen, Dai, and Guo (2023) use data from the China Household Finance Survey to demonstrate that higher levels of advanced financial literacy substantially increase the likelihood of stock market participation, with an additional point in the advanced financial literacy score raising the probability by approximately 12 percentage points. Hsiao and Tsai (2018) utilize data from the 2011 National Financial Literacy Surveys in Taiwan and find that individuals with higher financial literacy levels are more likely to purchase derivative products.

In Italy, studies have revealed low levels of financial literacy. Using the Italian Literacy and Financial Competence Survey (IACOFI), conducted by the Bank of Italy in early 2017, di Salvatore et al. (2018) highlight a significant gap in financial literacy between Italy and other G20 countries, particularly among less educated individuals, the elderly, and women. Similarly, using the 2020 Bank of Italy's second IACOFI, D'Alessio et al. (2021) document that the financial literacy of Italians lags behind by international standards and varies across different population groups. They confirm their results using some waves of the SHIW data. Their findings are consistent with earlier evidence from Guiso and Jappelli (2005) who, using the 1995 and 1998 SHIW surveys, show that non-awareness of financial products helps explain the stock-holding puzzle. They observe limited direct stock holding among Italian households during that period, with market participation increasing over time and being correlated with household resources, education levels, and geographical characteristics. Gallo and Sconti (2023) use the 2016 SHIW survey and show that financial literacy influences the values and inequality levels of Italian household income and wealth. This paper contributes to understanding the effects of a government's household-oriented bond policy on Treasury Bond market participation and quantifies the differential impact of financial literacy on this participation.

This paper will also contribute to the fast-developing literature on CBDC. While most of the literature focuses on the effects of CBDC on the financial sector, there is little work examining potential CBDC demand. For instance, Li (2023) investigates household demand for CBDC in Canada. Using a structural demand model applied to survey data, she estimates that CBDC could account for 4% to 52% of household liquid assets, depending on how it compares to cash and deposits in terms of features like anonymity, usefulness for budgeting, and bundling with banking services. Moreover, her study highlights that allowing banks to respond to CBDC could significantly constrain its adoption.

Using survey data in the Netherlands, Bijlsma et al. (2021) analyze public adoption intentions for CBDC. Their findings suggest that consumers perceive CBDC as distinct from traditional bank accounts, with privacy, security, and trust in the central bank playing crucial roles in driving adoption. The study also suggests that interest rates and the design of CBDC could influence public adoption and usage. In another work, Huynh et al. (2020) develop a structural model of demand for payment instruments and explore how consumers might use CBDC for point-of-sale payments, examining how payment method attributes influence consumer choices. Similarly, Nocciola and Zamora-Pérez (2024) assess transactional demand for CBDC at the point of sale, using a structural model of payment adoption and usage. They focus on the frictions associated with CBDC adoption, such as information barriers and the gradual diffusion of digital payment methods, and emphasize the importance of optimal CBDC design, information campaigns, and network effects in boosting CBDC demand.

While Huynh et al. (2020) and Nocciola and Zamora-Pérez (2024) focuses on the CBDC's role as a means of payments, this study considers a CBDC useful for both transactional and store-of-value purposes, similarly to Li (2023). However, unlike her work, this paper contributes to the understanding of how heterogeneity in households' financial literacy affects CBDC demand. Additionally, I explore how agents with different levels of financial literacy adjust their portfolio choices, including CBDC demand, when facing uncertainty. The findings will provide new insights to policymakers on how to design an effective CBDC that reaches the broader public.

The rest of the paper is organized as follows. Section 2 outlines the institutional background of the Italian government bond market. Section 3 describes the data used in the empirical exercise. Section 4 presents the empirical regression and its results. Section 5 describes the theoretical framework and portfolio choices following CBDC introduction. Section 6 concludes.

2 Italian Government Bond Market

This section outlines the Italian institutional background. The landscape of Italian government securities is diverse. Four broad categories of securities are available to private and institutional investors: Treasury Bills, Zero Coupon Bonds, Treasury Certificates, and Treasury Bonds.[3] This work focuses on Treasury Bonds (i.e., In Italian, *Buoni del Tesoro Poliennali* (*BTPs*), which translates to Treasury Bonds with long-term maturity). Treasury Bonds are a core part of Italy's public debt structure. As of the end of 2011, *BTPs* represented 66.47% of the total Italian government securities market [Ministero dell'Economia e delle Finance (2011)].

To boost domestic holding of its debt, in March 2012 the Italian government introduced retail Treasury Bonds which are available to retail investors only. The first retail Treasury Bonds were named *Italia*, followed by *Futura* in 2020 and *Valore* in 2023. Besides being available exclusively to retail investors, retail Treasury Bonds differ from standard ones by offering a final bonus to whoever purchases them during the placement period and holds them until maturity. Additionally, the issuance of the last two retail Treasury Bonds introduced, *Futura* and *Valore*, provides nominal coupons increasing over time, calculated based on a preset path of increasing rates over time (i.e., a "step-up" mechanism). Table 1 reports the characteristics of both standard and retail Treasury Bonds.

Table 1: Treasury Bonds (*BTPs*) in Italy

	Standard	Retail		
		Italia	*Futura*	*Valore*
Maturity	3-50 years	4-8 years	8-16 years	4-6 years
Coupon	Floating semi-annual	Semi-annual	Fixed semi-annual	Fixed
Yield	Avg. 3.86%	Min. 2% indexed to inflation	"Step-up" mechanism: 1.15% (1.3%) [1.45%] for the first 4y (middle 3y) [last 2y]	"Step-up" mechanism: 3.25% (4%) for the first 3y (last 3y)
Final bonus	✗	✓	✓(linked to GDP)	✓

This table compares the types of retail Treasury Bonds among themselves and with the standard Treasury Bonds. The standard *BTP* yield refers to the year 2023 and represents the weighted average interest rate. All Treasury Bonds have a minimum denomination of 1,000 euros and are subject to a 12.5% tax rate. *Source*: Italian Ministry of Economy and Finance.

Since their introduction, retail Treasury Bonds have received a positive response from retail investors. For instance, the most recent retail Treasury Bond, *Valore*, saw a constant positive take-up since its first issuance. The first issue in June 2023 attracted over 18.1 billion euros with approximately 650,000 contracts; the second issue in October 2023 raised 17.2 billion euros with around 642,000 contracts, and the third issuance in February 2024 ended

[3] Table 5 in Appendix A summarizes the differences among government securities in terms of maturity, remuneration, and auction type.

with 18.3 billion euros and $656,369$ contracts, marking the highest result ever recorded in terms of the amount subscribed and contracts concluded in a single issuance of government bonds dedicated to retail investors.[4]

This analysis will focus on the introduction of retail Treasury Bonds *Italia* in 2012 to study the effects on participation in the Treasury Bond market, as the major impact can likely be observed immediately following the release of the new financial instrument. Since its first issuance in March 2012, the total take-up of Treasury Bonds *Italia* amounts to 193.1 billion euros over a total of nineteen issuances.

3 SHIW Data

To study the effect on market participation of the new financial instrument, I use data from the Bank of Italy's Survey on Household Income and Wealth (SHIW) on the incomes and savings of Italian households. The survey was conducted from 1960 to 1987 at yearly intervals on repeated cross-section observations. Starting from 1989, the survey runs every other year (except for 1998 and 2020) on repeated cross-section observation and panel households. The panel component of the sample consists of all households participating from at least two waves and an additional part randomly selected from those interviewed only in the previous edition.

The SHIW sample includes approximately $8,000$ households per wave, with around $4,000$ being panel households. The sample is designed to represent the Italian population, excluding people living in institutions or residing in the country illegally. In this section, I describe the data using the 2008, 2010, 2012, 2014, 2016, and 2020 waves.

In the 2020 survey, a new sampling scheme was introduced to improve the quality of estimators for economic analysis. This structural change requires the adoption of specific weighting techniques for historical comparison with previous editions. More specifically, sampling weights were constructed using a statistical rebalancing technique [i.e., raking, see Kalton and Flores-Cervantes (2003)] that assigns each household interviewed in 2020 the same probability of being interviewed as under the previous design. Throughout the paper, all the descriptive statistics are computed using the sampling weights.

Each survey is conducted the year following the year wave. For example, the 2012 survey was administered in 2013. A typical question asked in the 2012 survey is

[4]See Ministero dell'Economia e delle Finance (2023a), Ministero dell'Economia e delle Finance (2023b), and Ministero dell'Economia e delle Finance (2024). The fourth issuance in May 2024 saw a decline in the public response, with 11.2 billion euros and $384,295$ contracts. This lesser response may be attributed to the anticipated cut in key interest rates by the European Central Bank.

Did you or a member of the household have any of the following [financial assets] *on 31 December 2012*: . . . .

Besides information on incomes and savings, the survey also provides information on household geographical and personal characteristics. Over the years, the survey has expanded to include wealth and various aspects of household economic behavior, such as financial assets and liabilities, and questions on financial knowledge.

3.1 Financial assets

To investigate households' financial market participation, I construct five classes of financial assets as specified in Table 2.[5] Real estate is excluded from the asset classes. Real estate is relatively important as a financial investment for many Italians, who often buy second houses as an investment. Considering the real estate equity value resulting from the difference between the value of the owned property and the debt incurred to buy it, real estate amounts to 80% of the average financial asset investments in the data and this fraction remains constant for most of the sample. However, real estate includes the sum of all real estate, such as the primary residence, secondary houses (potentially rented out), commercial buildings, and lands. While it is possible to distinguish between primary residences and other properties, the associated debt for purchasing these properties is only available in aggregate form. Therefore, this analysis focuses exclusively on purely financial assets.

As anticipated in Section 2, the analysis focuses on household participation in the Treasury Bond market, the highlighted category of government bonds in Table 2.

Figure 1 illustrates the average market participation of Italian households across the waves. Households show a significant preference for traditional financial assets, with consistently high participation in deposits, which is reported on the left vertical axis. Participation in government bonds is relatively stable, with a similar trend to private bonds. Participation in more complex financial instruments, such as managed investment schemes and shares remains low throughout most of the sample period, with a slight increase in the last wave.

Figure 2 provides a detailed breakdown of participation in government securities. While overall participation in government securities generally declines over time across most categories, Treasury Bonds (*BTPs*) exhibit a slight positive trend, confirming the evidence that Italians have a preference for long-term government bonds [Ferrara et al. (2024), Pavot and

[5]The SHIW contains information on other financial assets excluded from the analysis as their individual magnitude is small, i.e., Foreign securities, loans to cooperatives, private pensions, insurance policies for life and health, against accidents.

Table 2: Financial asset classes

Class	Name	Individual Assets in SHIW
Deposits	DEP	Bank current and saving accounts, CDs, repos, postal savings certificates
Government Bonds	GBONDS	*BOTs*, *CCTs*, *CTZs*, ***BTPs***, other Italian government securities
Private Bonds	PBONDS	Privately issued bonds
Managed Investment Schemes	MIS	Managed funds shares, managed savings
Shares	SHARES	Shares

This table details individual assets in SHIW, grouped in classes. *Buoni del Tesoro Ordinari (BOTs)* correspond to Treasury Bills, *Certificato di Credito del Tesoro (CCTs)* correspond to Treasury Certificates, *Certificato del Tesoro Zero-coupon (CTZs)* correspond to Zero-coupon Bonds, and *Buoni del Tesoro Poliennali (BTPs)* correspond to Treasury Bonds with long-term maturity.
The composition of macro classes may change over time based on whether questions about the ownership of specific assets have been included in the respective surveys. When occurring, the change is incremental, with new asset subclasses being added to the particular asset class and compositional changes only impacting previous measures. In general, these changes will not qualitatively affect the analysis results.
Source: SHIW and author calculations.

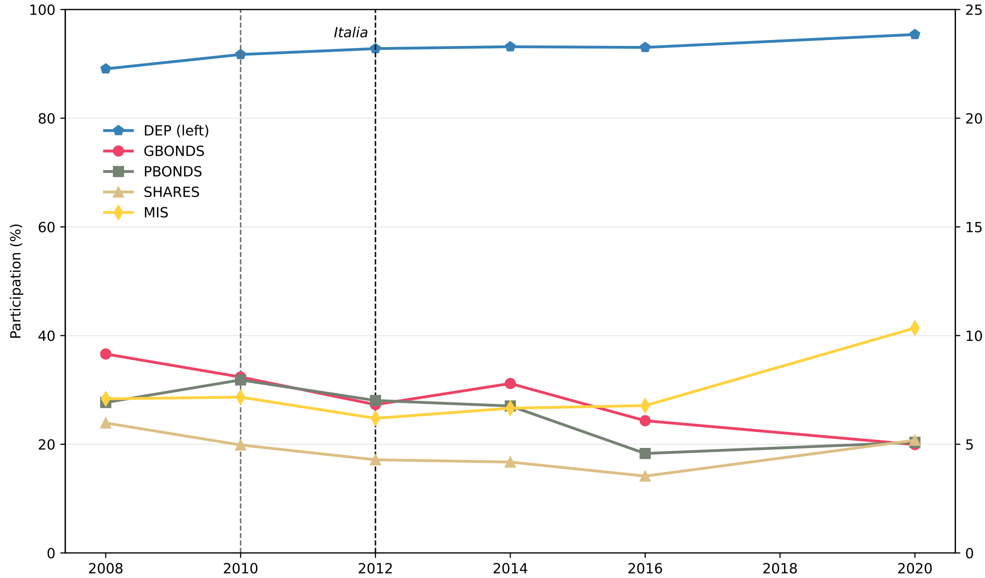
Valenta (2021)]. Notably, there is an increase in participation in the Treasury Bond market from 2010 to 2012, which can be attributed to the introduction of *BTP Italia* in 2012.[6]

3.2 Financial literacy

Hastings, Madrian, and Skimmyhorn (2013) define financial literacy as "the ability to use knowledge and skills to manage one's financial resources effectively for lifetime financial security", while other definitions refer to knowledge of financial concepts or products. Financial literacy measures in the literature encompass various methodologies and indicators to assess individuals' comprehension of fundamental financial concepts. One of the most common ways to identify financially literate respondents is based on their accurate responses to the "Big Three" questions [see, e.g., Gallo and Sconti (2023)], as defined by Lusardi and Mitchell (2014), which capture the basic financial concepts of interest, inflation, and risk diversification. These questions assess essential financial knowledge by testing individuals' understanding of how interest compounds over time, the effects of inflation on purchasing power, and the importance of diversifying investments to mitigate risk. Together, they provide a concise measure of financial literacy that is widely used in research to gauge people's capability to make sound financial decisions.

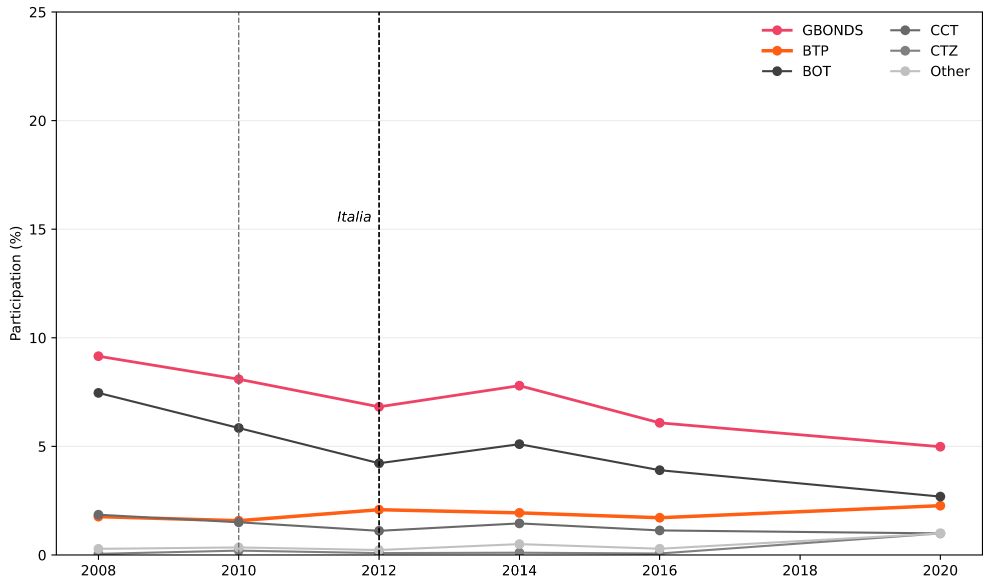
[6]Recall that the 2012 survey was administered in 2013. Therefore, participation in 2012 reflects the end of the year, influenced by the introduction of the first retail Treasury Bonds *Italia* in March 2012.

Figure 1: Market participation of Italian households



This figure shows market participation across the sample of Italian households. Weighted average of the observations.
Source: SHIW.

Figure 2: Government securities participation of Italian households



This figure shows the breakdown of government securities participation across the sample of Italian households. Weighted average of the observations.
Source: SHIW.

Other measures of financial literacy in the literature include the number of correct responses to the "Big Five" questions proposed by Hastings, Madrian, and Skimmyhorn (2013), emphasizing a broader scope of financial knowledge [see, e.g., Angrisani et al. (2023)]. D'Alessio et al. (2021) adopt the OECD methodology and construct the financial literacy score from assessments of knowledge, behavior, and attitude. Using the Cronbach coefficient, the authors ascertain the reliability of indicators aggregating responses across various questions. Notably, they find that the most reliable indicator is financial knowledge, which captures the basic financial concepts reflected in the "Big Three" questions.

Since 2006, SHIW has collected information on household financial knowledge (except for the 2012 and 2014 waves).[7] The questions vary in number and content over time. However, the "Big Three" questions are consistently present across the waves. The question related to interest rates appears in the 2006, 2016, and 2020 waves; the question regarding risk diversification is asked in the 2008, 2010, 2016, and 2020 waves; and the question about inflation is present in all the waves considered in the analysis. Additionally, the survey includes a question assessing the financial knowledge of mortgages in the 2006, 2008, and 2010 waves. In the 2006 wave, financial literacy questions were asked to a subset of families, therefore I do not include this wave in the statistics.

Figure 3 shows the aggregate percentage of correct responses to financial literacy questions and the average number of correct answers across the cross-section of households in different waves of the SHIW. Compared to responses to other questions, the inflation question consistently has higher correct responses, particularly in 2008 and 2010, though it shows a decline in 2020. The risk diversification question has lower correct response rates, peaking in 2020. The interest rate question shows correct response rates of around 50% in the last two waves. The mortgage question, included in the earlier waves, shows relatively high correct response rates, especially in 2008. The average number of correct answers indicates a stable level of financial literacy over time, with slight fluctuations.[8]

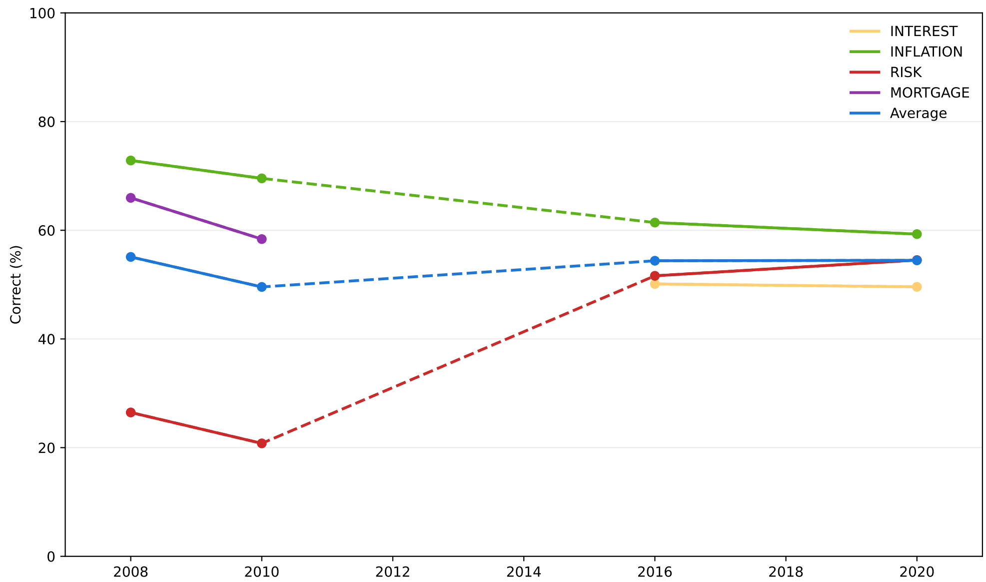
I define the financial literacy score as the number of correct answers to the financial literacy questions. Each wave includes a different combination of three questions, so the financial literacy score can have four levels: 0 if the household does not answer any question correctly, 1 if there is one correct answer, 2 if there are two correct answers and 3 if all answers are correct.

Similar to Figures 1 and 2 in Section 3.1, Figures 4 and 5 report the overall market participation and participation in government securities, respectively, distinguishing between financial literacy score levels. Figure 4 suggests that households with higher financial literacy

[7]See Appendix A.1 for the exact formulation of the questions.

[8]See Table 6 in Appendix A for the percentage numbers of correct responses.

Figure 3: Correct responses to financial literacy question



This figure shows the aggregate percentage of correct responses to financial literacy questions. Incorrect responses include "Don't know" and "No answer". The average refers to the average number of correct answers.
Source: SHIW.

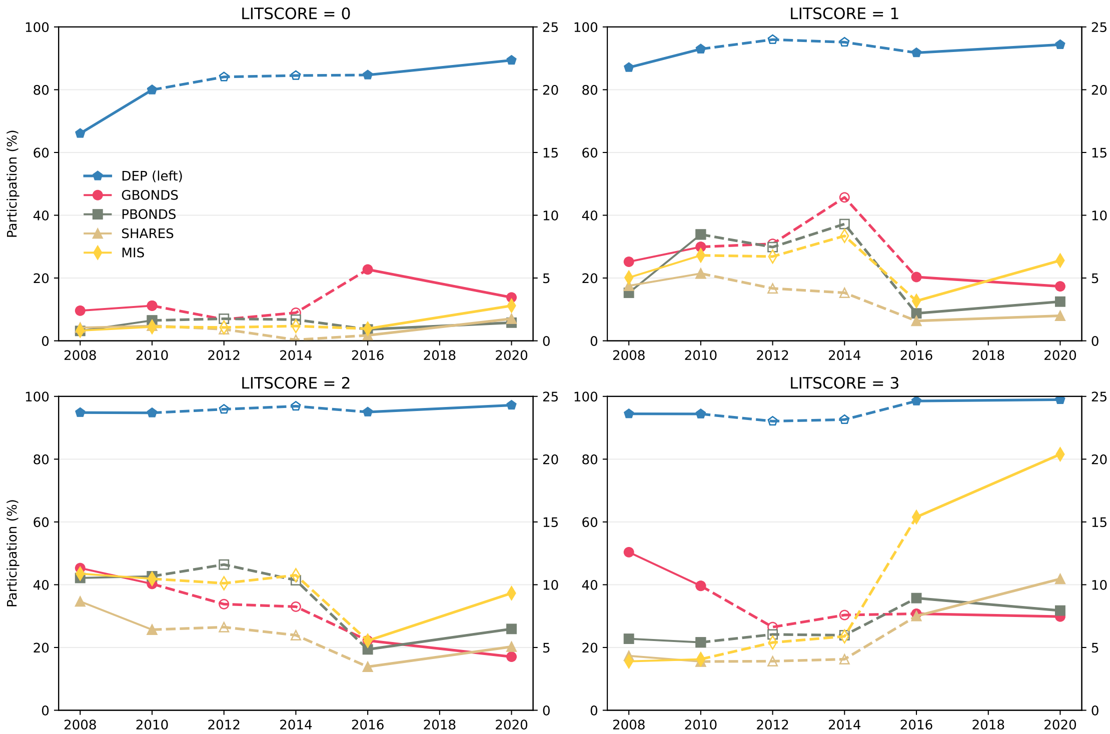
scores tend to have more diversified portfolios. While deposit participation is high across all literacy levels, households with higher literacy scores exhibit greater participation in other financial markets. These considerations hold when looking at the breakdown by government securities in Figure 5. Focusing on the Treasury Bond market, participation differs across financial literacy levels. This evidence underscores the role of financial literacy in influencing investment decisions.

Finally, Figure 6 shows the percentage of households by financial literacy score level in every wave since 2008, excluding 2012 and 2014 where the financial literacy questions were not included. Over time, there is an increasingly balanced number of households by financial literacy level.

4 Retail Treasury Bonds and market participation

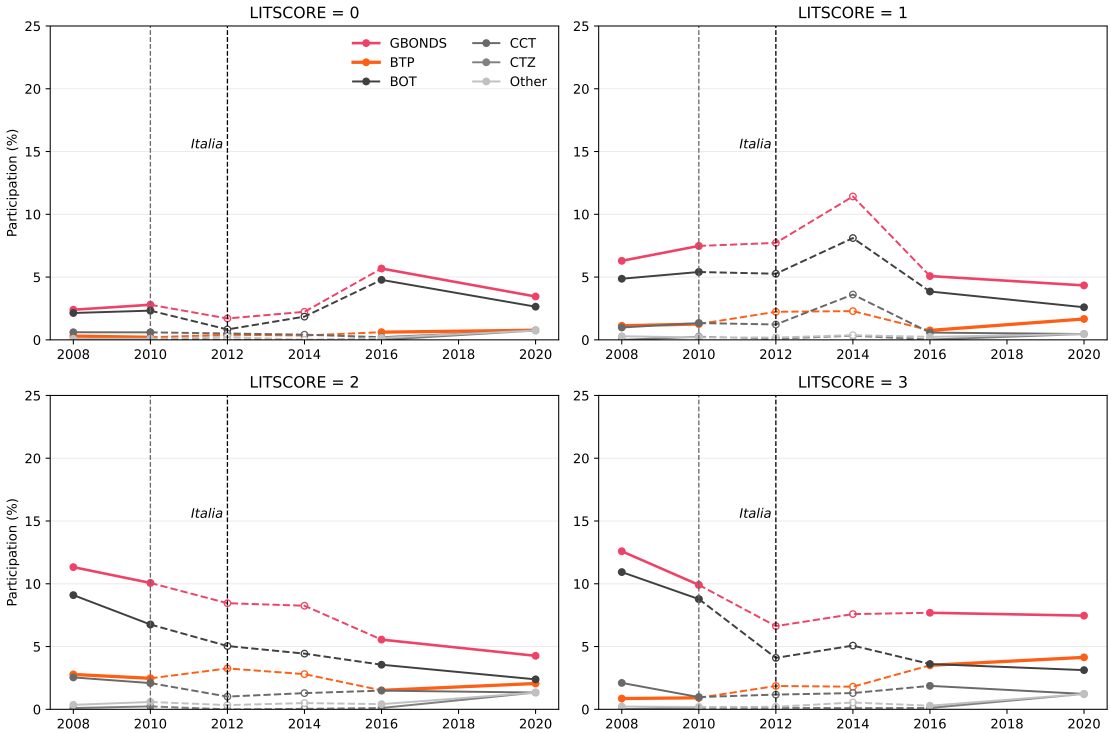
This section evaluates the effect of the introduction of retail Treasury Bonds on household participation in the Treasury Bond market. As household financial behavior is affected by financial literacy, the empirical model quantifies the differential treatment-financial literacy effect. The policy/treatment used is the introduction of retail Treasury Bonds *Italia* in March 2012. These are the first retail Treasury Bonds issued, and, likely, the major effects of the

Figure 4: Market participation by literacy score level



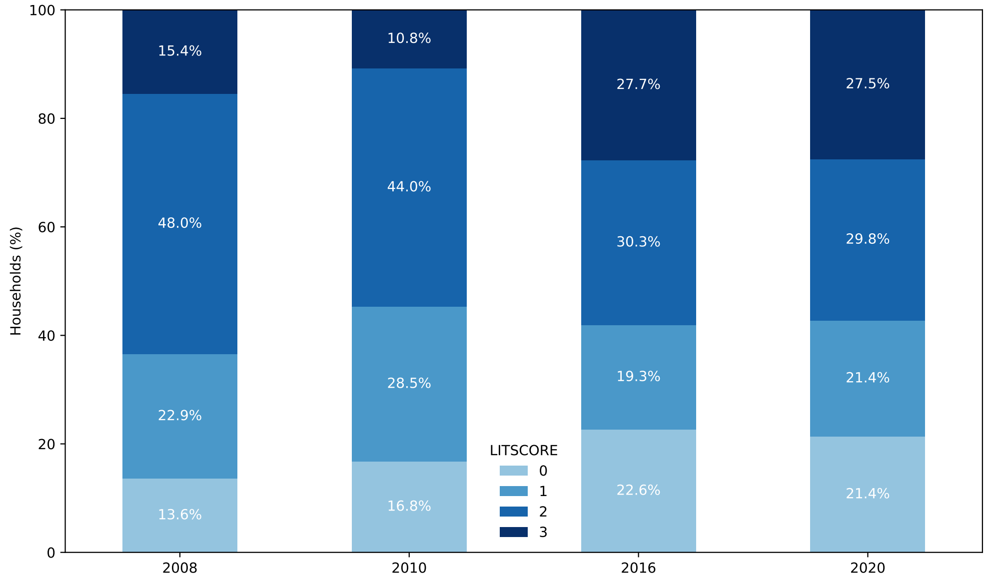
This figure shows market participation across the sample of Italian households, distinguishing between financial literacy score levels. When the information on household literacy scores is missing for a specific year, the last data available are used. Weighted average of the observations.
Source: SHIW.

Figure 5: Government securities participation by literacy score level



This figure shows the participation in government securities markets across the sample of Italian households, distinguishing between financial literacy score levels. When the information on household literacy scores is missing for a specific year, the last data available are used. Weighted average of the observations.
Source: SHIW.

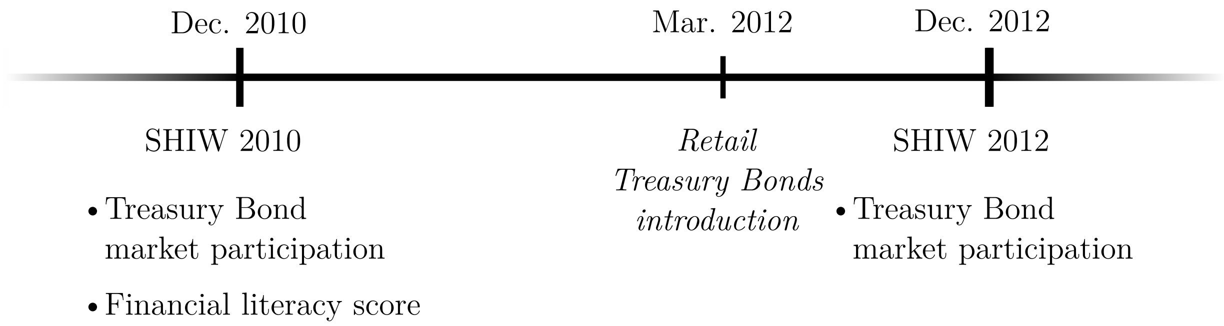
Figure 6: Percentage of households by financial literacy score level



This figure shows the percentage of households by financial literacy score level.
Source: SHIW.

retail government policy on market participation can be seen right after their introduction. I conduct a short-run analysis using data from the 2010 and 2012 SHIW waves, where the household's initial level of financial literacy is the one in 2010, and the policy is introduced in March 2012 (recall that the 2012 survey was run in 2013). Figure 7 shows the timeline of the policy introduction and the data. The panel dimension of the data allows me to follow the investment behavior of the same household over time.

Figure 7: Timeline of the short-run analysis



A traditional empirical challenge is the reverse causality: Households with higher wealth may have more opportunities and incentives to acquire financial skills and, in turn, increase their wealth [Lusardi, Michaud, and Mitchell (2017)]. Exploiting the longitudinal dimension of the dataset, I circumvent the problem of reverse causality: Household asset-holding decisions in 2012 cannot affect their level of financial knowledge in 2010.

From Figure 6 in Section 3.2, in 2010 financial literacy score level 3 only includes 10.8% of households, therefore I aggregate it with score level 2. This gives three literacy score levels that identify the same number of household types: 0 for financially illiterate, 1 for low-financial literate, and 2 for high-financial literate.

4.1 Baseline regression

I construct the empirical model using the Generalized Linear Model (GLM) framework, which extends linear regression to binary outcomes. The relationship between predictors and the outcome mean is modeled via a logistic link function, g. Let y_{it} denote the observed Treasury Bond market participation of household i at time t, where 1 indicates participation and 0 otherwise, and let $P_{it} = \mathbb{E}[y_{it}]$ represent the probability of participation. The probability P_{it} is determined by the latent variable z_{it}, which captures the propensity of the household to participate, through the logit link function:

$$z_{it} = g(P_{it}) \equiv \ln\left(\frac{P_{it}}{1 - P_{it}}\right). \tag{1}$$

The propensity z_{it} is modeled as:

$$z_{it} = \alpha + \beta(D_t^{12} \times LS_i^{10}) + \sum_{\ell=1}^{2} \gamma_\ell LS_{i\ell}^{10} + \epsilon_{it}, \quad t = 2010, 2012. \tag{2}$$

where the coefficient of interest, β, captures the interaction between the policy dummy D_t^{12}, which equals 1 in 2012, and the initial household financial literacy score level, LS_i^{10}. This score can take three values corresponding to the same number of household types: 0 if financially illiterate, 1 if low-financial literate, and 2 if high-financial literate. The natural propensity to participate for financial literacy level 0 is captured by α and group-fixed effects for each financial literacy level ℓ are accounted for by the γ_ℓ coefficients.

To provide an intuition for interpreting the estimated coefficient of interest $\hat{\beta}$, equation (2) can be rewritten as:

$$z = \hat{\beta}(D^{12} \times LS^{10}) + \mathscr{A}, \quad \mathscr{A} = \hat{\alpha} + \sum_{\ell=1}^{2} \hat{\gamma}_\ell LS_\ell^{10}, \tag{3}$$

where $\mathscr{A}$ includes the effects of the other predictors.

Recalling that the propensity to participated is estimated with a logistic function, as in equation (1), the differential treatment-financial literacy effects when the interaction term

$D^{12} \times LS^{10}$ is equal to 1 and 0 are, respectively:

$$\ln\left(\frac{P_1}{1-P_1}\right) = \hat{\beta} + \mathscr{A}, \qquad \ln\left(\frac{P_0}{1-P_0}\right) = \mathscr{A}. \tag{4}$$

By taking the difference, I obtain an expression that relates the probabilities of participation only to the coefficient of the policy-literacy term and is independent of $\mathscr{A}$:

$$\ln\left(\frac{P_1}{1-P_1}\right) - \ln\left(\frac{P_0}{1-P_0}\right) = \hat{\beta}. \tag{5}$$

Taking exponents on both sides gives the odds ratio:[9]

$$\frac{P_1}{1-P_1} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}). \tag{6}$$

For the high-financial literate household, when $D^{12} \times LS^{10} = 2$, the odds ratio can be evaluated as:

$$\frac{P_2}{1-P_2} = \frac{P_1}{1-P_1} \times \exp(\hat{\beta}) = \frac{P_0}{1-P_0} \times \exp(2\hat{\beta}), \tag{7}$$

where $\exp(\hat{\beta})$ represents the multiplicative change in the odds (i.e., the odds ratio) for each one-unit increase in the treatment-financial literacy interaction $D^{12} \times LS^{10}$.

The intuition is that, after introducing retail Treasury Bonds, each higher level of financial literacy score changes the odds of participating in the Treasury Bond market by $\exp(\hat{\beta})$ compared to the level below. Specifically, if $\exp(\hat{\beta})$ is greater than 1, it implies an increase in the odds, whereas a value less than 1 indicates a decrease in the odds.

4.2 Financial literacy score dummies regression

Alternatively, to explore potential non-linear relationships across financial literacy levels, I model the household i propensity to participate z_{it} as

$$z_{it} = \alpha + \sum_{\ell=1}^{2} \beta_\ell (D_t^{12} \times LS_{i\ell}^{10}) + \sum_{\ell=1}^{2} \gamma_\ell LS_{i\ell}^{10} + \epsilon_{it}, \quad t = 2010, 2012. \tag{8}$$

with $LS_{i\ell}^{10}$ being household financial literacy score dummies for each score level ℓ, where the illiterate (i.e., score level 0) are the baseline.

[9] The odds of an outcome occurring is the ratio of successes to failures.

The estimated coefficients of interest, $\hat{\beta}_\ell$, can be interpreted through the odds ratio:

$$\frac{P_\ell}{1-P_\ell} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}_\ell), \quad \ell = 1, 2. \tag{9}$$

For instance, for the high-financial literate group (i.e., $\ell = 2$):

$$\frac{P_2}{1-P_2} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}_2). \tag{10}$$

The intuition is analogous to before: Following the introduction of retail Treasury Bonds, the odds of a high-financial literate household participating in the Treasury Bond market is $\exp(\hat{\beta}_2)$ times higher compared to the financial illiterate household baseline.

As previously mentioned, the main aim of the empirical investigation is to explore if and how financial literacy influenced households' participation in the Treasury Bond market following the introduction of the new instrument. If so, it is interesting to investigate the potential household portfolio reallocation. Therefore, participation in government securities other than Treasury Bonds and stock-holdings are considered alternative output variables.

4.3 Results

Table 3 reports the estimated differential changes in the odds of participating. Recall that the baseline specification (2) uses financial literacy score level for illiterate, low-literate, and high-literate. In the SHIW data, the percentage of households participating in the Treasury Bond market at the end of 2010 was 1.58%. After introducing retail Treasury Bonds, each higher level of financial literacy score increases the odds of participating in the Treasury Bond market by 17%.[10] When considering alternative market participation dependent variables, each level increase in the financial literacy score decreases the odds of participating in the market for other government securities by 19%. The odds of stock-holding decrease by 5% for each additional level of financial literacy score.

When considering the breakdown by financial literacy score level in the data, Treasury Bond market participation rates at the end of 2010 were 0.2%, 1.27%, and 2.15% for financially illiterate, low-financial literate, and high-financial literate, respectively. The results from specification (8) suggest that, after the new instrument introduction, as literacy increases, the magnitude of the effects on the odds of participating in the Treasury Bonds market also increases compared to the baseline for the financially illiterate. However, the rate of increase

[10]Table 7 in Appendix B reports the logit regression estimation results. Recall that the odds of participating change by, e.g., $\exp(\hat{\beta}) - 1 = \exp(0.16) - 1 = 17\%$.

is not monotone across financial literacy levels, as indicated by the coefficients of low and high literacy in the second and third lines in Table 3, respectively. While for the low-financial literate, the odds of participating in the Treasury Bond market increase by 82% compared to the financially illiterate, the increase is only 30% for the high-financial literate. Similarly, the decrease in the odds of stock-holdings, compared to the baseline of illiterate, is more pronounced for the low-literate. In contrast, the decrease is greater for the high-literate when considering participation in the market for other government securities.

In the specification (8), the individual coefficients for financial literacy level are not mutually significantly different. While the odds of participating increase from having zero financial literacy to having some degree of literacy, it is not possible to draw firm conclusions about the differential effects of financial literacy. Nevertheless, it is worth noticing that the financial literacy score is only an approximate measure of true financial literacy. The results suggest that different levels of financial literacy impact market participation.

Table 3: Changes in the odds of participation

Dep. Var.: Market Participation	Treasury Bond		Other Govt. Bond		Stocks	
	(2)	(8)	(2)	(8)	(2)	(8)
$D^{12} \times LS^{10}$	0.17***		−0.19***		−0.05**	
$D^{12} \times LS^{10}_1$		0.82**		−0.22*		−0.21***
$D^{12} \times LS^{10}_2$		0.30**		−0.34***		−0.09*

The table reports changes in the odds of participating. The changes are computed as

$$\exp(\hat{b}) - 1, \quad b \in \{\beta, \beta_\ell\},$$

where the coefficients β and β_ℓ are estimated using the Generalized Estimating Equations (GEE), an extension of GLM for panel data. The sample counts a panel of 4,611 households over a two-year period. Literacy level group-fixed effects and time-fixed effects are included.

In (2), the baseline financial literacy level is 0. * p < 0.1; ** p < 0.05; *** p < 0.01

To summarize, from the baseline regression (2), I find that financial literacy positively influenced participation in the Treasury Bond market after the introduction of retail Treasury Bonds. However, the effect is non-monotone across financial literacy levels, as shown in the results from the financial literacy score dummies specification (8). Comparing the second and third rows in Table 3, the low-financial literate households are more likely to participate in the Treasury Bond market compared to the other household groups. Furthermore, when using alternative dependent variables, results suggest a portfolio shift from other government bonds and stocks toward Treasury Bonds. Interestingly, from the last column in Table 3, following the new policy high-financial literate are less likely to decrease participation in the stock market compared to the other household group.

4.4 Robustness

As stated at the beginning of Section 4, the empirical model considers three financial literacy score levels mapping the same number of household types: 0 for financially illiterate, 1 for low-financial literate, and 2 for high-financial literate. This is because the number of households with high financial literacy is aggregated at a unique level. Alternatively, the specification considering all the financial literacy score levels available in the data is

$$z_{it} = \alpha + \beta(D_t^{12} \times LS_i^{10}) + \sum_{\ell=1}^{3} \gamma_\ell LS_{i\ell}^{10} + \epsilon_{it}, \quad t = 2010, 2012, \tag{11}$$

where the initial household financial literacy score level, LS_i^{10}, can have four values with progressively higher literacy.

Similarly, the specification with financial literacy score level dummies is

$$z_{it} = \alpha + \sum_{\ell=1}^{3} \beta_\ell(D_t^{12} \times LS_{i\ell}^{10}) + \sum_{\ell=1}^{3} \gamma_\ell LS_{i\ell}^{10} + \epsilon_{it}, \quad t = 2010, 2012. \tag{12}$$

with $LS_{i\ell}^{10}$ being household financial literacy score dummies for each score level ℓ.

Table 8 in Appendix B.1 reports the logit regression estimation results when considering more financial literacy score levels. The findings are analogous to Table 7.

5 A simple two-agent endowment economy

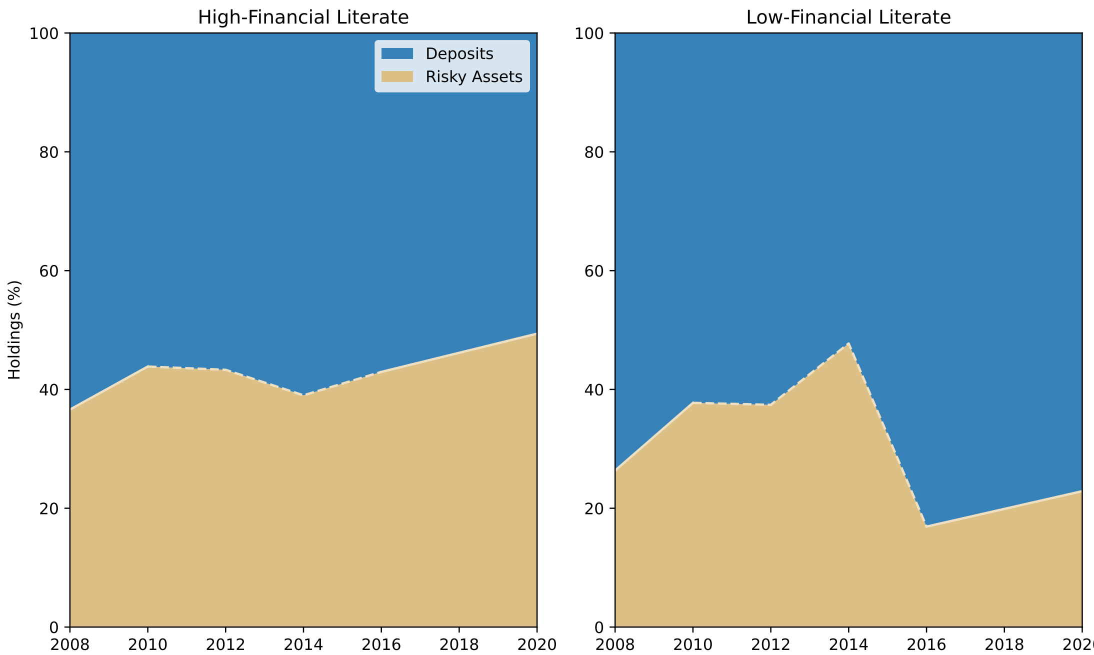
This section explores how households' financial literacy influences CBDC market participation. While CBDC could be accessible to everyone, its adoption depends on several factors, including household financial literacy. Since the CBDC market is not yet established, I focus on the demand for CBDC.

Given the lack of empirical data on CBDC usage, the introduction of retail Treasury Bonds serves as a proxy to investigate the effects of a retail CBDC. Both instruments are claims of the government, and they are aimed at households, making retail Treasury Bonds a suitable comparative instrument for a CBDC. Findings from the retail Treasury Bonds exercise in Section 4 suggest a differential investment behavior based on financial literacy, with households in the low-literate group being more likely to participate following the introduction of the new instrument compared to the financially illiterate and high-financial literate household groups.

Building on these empirical insights, I develop a two-agent endowment economy to analyze how CBDC demand may vary by financial literacy. In the theoretical model, I abstract from modeling the financially illiterate group, as I want to disentangle the potential different CBDC adoption conditional on the financial literacy level.

The economy is populated by two types of agents differentiated by their financial literacy: high-financial literate (HFL) and low-financial literate (LFL). The HFL agent can invest in risky assets and risk-free deposits, whereas the LFL agent is limited to deposits. This distinction between agent investment opportunities is motivated by empirical data. Figure 8 shows the portfolio composition across the average sample of Italian households, distinguishing between high and low financial literacy groups.[11]

Figure 8: Portfolio composition across Italian households



This figure shows the portfolio allocation across the avergae sample of Italian households, distinguishing between high and low literacy groups. High financial literacy corresponds to literacy score levels 2 and 3, and low financial literacy to literacy score level 1. The holdings are normalized such that deposits and risky assets together account for the entire portfolio. When the information on household literacy scores is missing for a specific year, the last data available are used.
Source: SHIW.

On average, HFL households tend to hold more risky assets than LFL households. Additionally, there is a downward trend in risky asset holdings among LFL households. The literature has shown that information costs help explain why some individuals choose not to hold risky assets [Vissing-Jorgensen (2004)]. The higher costs of processing financial information make LFL households more reluctant to invest in the risky asset market. To

[11]Risky assets include shares, managed investment schemes, and private bonds.

incorporate this aspect, in the model I consider the limit scenario where LFL agents do not hold any risky assets.

Each agent lives for two periods and receives an endowment y in the first period. In the second period, agents experience a stochastic income ϵ such that

$$\epsilon = \begin{cases} s_{\max} & \text{with probability } p^{\epsilon}, \\ s_{\min} & \text{with probability } 1 - p^{\epsilon}. \end{cases} \tag{13}$$

In the portfolio choice analysis, I will consider cases with negative minimum income $s_{\min}$, which represented a loss of the income source and unexpected cost in the second part of agents' working life.

Agents maximize their discounted expected lifetime utility, $\mathbb{E}[\mathscr{U}]$, subject to a set of budget constraints for each period. Each agent values liquidity services derived from holding financial assets. Assume additively separable and concave utility.

5.1 Pre-CBDC economy

In the pre-CBDC economy, both agents can access risk-free deposits. Assuming log-utility:

$$\mathbb{E}[\mathscr{U}] = \ln(c_1) + \beta \mathbb{E} \ln(c_2) + \gamma \ln \Big(z(d) \Big), \tag{14}$$

where c_1 and c_2 are consumption in the the first and second period and $\beta \in (0, 1)$ is the discount factor. The last term captures the liquidity benefits of holding deposits, with $\gamma \geq 0$ liquidity preference parameter, and liquidity services z function of deposits d with return $R^d > 1$:

$$z(d) = R^d d. \tag{15}$$

5.1.1 High-financial literate agent problem

The HFL agent can invest in risk-free deposits and risky assets a with stochastic return R^a such that

$$R^a = \begin{cases} \bar{R}^a > R^d & \text{with probability } p^a, \\ \underline{R}^a < 1 & \text{with probability } 1 - p^a, \end{cases} \tag{16}$$

where $\bar{R}^a$ and $\underline{R}^a$ are the maximum and minimum return, respectively.

The HFL agent's budget constraints in the first and second periods are:

$$c_1^h + a + d^h = y, \tag{17}$$
$$c_2^h = R^a a + R^d d^h + \epsilon. \tag{18}$$

The HFL agent maximizes the discounted expected lifetime utility

$$\begin{aligned}\mathbb{E}[\mathscr{U}] = \ln(y - a - d^h) + \beta \Big\{ & p^a \left[p^\epsilon \ln(\bar{R}^a a + R^d d^h + s_{\max}) + (1 - p^\epsilon) \ln(\bar{R}^a a + R^d d^h + s_{\min}) \right] \\ & + (1 - p^a) \left[p^\epsilon \ln(\underline{R}^a a + R^d d^h + s_{\max}) + (1 - p^\epsilon) \ln(\underline{R}^a a + R^d d^h + s_{\min}) \right] \Big\} \\ & + \gamma \ln(R^d d^h),\end{aligned} \tag{19}$$

by choosing optimal quantities of assets a and d^h.

Note that there is an implicit constraint due to the domain of the logarithmic utility function such that the problem is well defined only when

$$\underline{R}^a a + R^d d^h + s_{\min} > 0\,. \tag{20}$$

This mathematical constraint reflect the need of the agent to hedge against the worst-case scenario of a negative return on the risky asset investments combined with a negative cost in the second period, regardless of the probability of this event.

The first-order condition for risky assets, $\frac{\partial \mathbb{E}[\mathscr{U}]}{\partial a} = 0$, is:

$$\begin{aligned}\frac{1}{y - a - d^h} = \beta \Bigg\{ & \bar{R}^a p^a \left[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\max}} + \frac{1 - p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\min}} \right] \\ & + \underline{R}^a (1 - p^a) \left[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1 - p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\min}} \right] \Bigg\}.\end{aligned} \tag{21}$$

The first-order condition for deposits, $\frac{\partial \mathbb{E}[\mathscr{U}]}{\partial d^h} = 0$, is:

$$\begin{aligned}\frac{1}{y - a - d^h} = \beta R^d \Bigg\{ & p^a \left[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\max}} + \frac{1 - p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\min}} \right] \\ & + (1 - p^a) \left[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1 - p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\min}} \right] \Bigg\} + \frac{\gamma}{d^h}.\end{aligned} \tag{22}$$

5.1.2 Low-financial literate agent problem

The LFL agent has access only to deposits and faces the following budget constraints in the first and second periods, respectively:

$$\begin{aligned} c_1^l + d^l =& y, \quad (23) \\ c_2^l =& R^d d^l + \epsilon. \quad (24) \end{aligned}$$

The LFL agent maximizes the discounted expected lifetime utility

$$\mathbb{E}[\mathscr{U}] = \ln(y - d^l) + \beta \left[p^\epsilon \ln(R^d d^l + s_{\max}) + (1 - p^\epsilon) \ln(R^d d^l + s_{\min})\right] + \gamma \ln(R^d d^l), \quad (25)$$

by choosing the optimal quantity of deposits d^l.

In this case, the implicit constraint due to the domain of the logarithmic utility function is

$$R^d d^l + s_{\min} > 0\,. \quad (26)$$

The first-order condition, $\frac{\partial \mathbb{E}[\mathscr{U}]}{\partial d^l} = 0$, is:

$$\frac{1}{y - d^l} = \beta R^d \left[\frac{p^\epsilon}{R^d d^l + s_{\max}} + \frac{1 - p^\epsilon}{R^d d^l + s_{\min}}\right] + \frac{\gamma}{d^l}. \quad (27)$$

5.2 CBDC economy

The government introduces a CBDC accessible to both types of households, interest-bearing, and offering liquidity benefits. Importantly, the relation between financial instrument returns is as follows:

$$\mathbb{E}[R^a] > R^d \geq R^m > 1, \quad (28)$$

such that the expected return on the risky asset, $\mathbb{E}[R^a]$, is greater than the return on risk-free deposits, R^d, which in turn is assumed to be higher than or equal to the return on CBDC, R^m.

Agents' discounted expected lifetime utility is now assumed to follow:

$$\mathbb{E}[\mathscr{U}] = \ln(c_1) + \beta \mathbb{E} \ln(c_2) + \gamma \ln\Big(z(d, m)\Big),$$

where liquidity services z are a function of deposits d and CBDC m, as defined by:

$$z(d,m) = \left[(R^d d)^{1-\sigma} + \lambda(R^m m)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{29}$$

In equation (29), CBDC and deposits are imperfect substitutes, with $\sigma \geq 0$ representing the inverse elasticity of substitution between the two liquid assets.[12] The parameter $\lambda \geq 0$ indexes the liquidity benefits of CBDC relative to deposits, reflecting factors such as privacy or convenience of use.

5.2.1 High-financial literate agent problem with CBDC

With CBDC, the HFL agent's budget constraints are:

$$c_1^h + a + d^h + m^h = y, \tag{30}$$

$$c_2^h = R^a a + R^d d^h + R^m m^h + \epsilon. \tag{31}$$

The HFL agent maximizes the discounted expected lifetime utility

$$\begin{aligned}
\mathbb{E}[\mathcal{U}] = \ln(y - a - d^h - m^h) + \beta \Big\{ & p^a \Big[p^\epsilon \ln(\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}) \\
& \quad + (1-p^\epsilon) \ln(\bar{R}^a a + R^d d^h + R^h m^h + s_{\min})\Big] \\
& + (1-p^a) \Big[p^\epsilon \ln(\underline{R}^a a + R^d d^h + R^m m^h + s_{\max}) \\
& \quad + (1-p^\epsilon) \ln(\underline{R}^a a + R^d d^h + R^m m^h + s_{\min})\Big] \Big\} \\
& + \gamma \ln\Big(z(d^h, m^h)\Big),
\end{aligned} \tag{32}$$

by choosing optimal quantities of assets a, d^h and m^h.

With CBDC, the implicit constraint due to the domain of the logarithmic utility function reads

$$\underline{R}^a a + R^d d^h + R^m m^h + s_{\min} > 0\,. \tag{33}$$

[12] Several studies in the literature consider imperfect substitutability between CBDC and deposits [see, e.g., Agur, Ari, and Dell'Ariccia (2022), Bacchetta and Perazzi (2022), Barrdear and Kumhof (2022), Burlon, Muñoz, and Smets (2024), Chen and Filippin (2024), Kumhof and Noone (2021), and Niepelt (2024)].

The first-order conditions for risky assets, deposits, and CBDC are, respectively:

$$
\begin{aligned}
a: \qquad \frac{1}{y-a-d^h-m^h} =& \beta\Bigg\{\bar{R}^a p^a\Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg] \\
&+ \underline{R}^a(1-p^a)\Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\max}} + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg]\Bigg\},
\end{aligned} \tag{34}
$$

$$
\begin{aligned}
d^h: \qquad \frac{1}{y-a-d^h-m^h} =& \beta R^d\Bigg\{p^a\Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg] \\
&+ (1-p^a)\Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg]\Bigg\} \\
&+ \gamma\Bigg[\frac{(R^d d^h)^{-\sigma}}{(R^d d^h)^{1-\sigma} + \lambda(R^m m^h)^{1-\sigma}}\Bigg],
\end{aligned} \tag{35}
$$

$$
\begin{aligned}
m^h: \qquad \frac{1}{y-a-d^h-m^h} =& \beta R^m\Bigg\{p^a\Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg] \\
&+ (1-p^a)\Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}}\Bigg]\Bigg\} \\
&+ \gamma\lambda\Bigg[\frac{(R^m m^h)^{-\sigma}}{(R^d d^h)^{1-\sigma} + \lambda(R^m m^h)^{1-\sigma}}\Bigg].
\end{aligned} \tag{36}
$$

5.2.2 Low-financial literate agent problem with CBDC

Now the LFL agent can access a new financial instrument. Their budget constraints are:

$$c_1^l + d^l + m^l = y, \tag{37}$$

$$c_2^l = R^d d^l + R^m m^l + \epsilon. \tag{38}$$

The LFL agent maximizes the discounted expected lifetime utility

$$
\begin{aligned}
\mathbb{E}[\mathscr{U}] =& \ln(y - d^l - m^l) + \beta\left[p^\epsilon \ln(R^d d^l + R^m m^l + s_{\max}) + (1-p^\epsilon)\ln(R^d d^l + R^m m^l + s_{\min})\right] \\
&+ \gamma \ln\Big(z(d^l, m^l)\Big),
\end{aligned} \tag{39}
$$

by choosing optimal quantities of d^l and m^l.

The implicit constraint due to the domain of the logarithmic utility function is

$$R^d d^l + R^m m^l + s_{\min} > 0\,. \tag{40}$$

The first-order conditions for deposits and CBDC are, respectively:

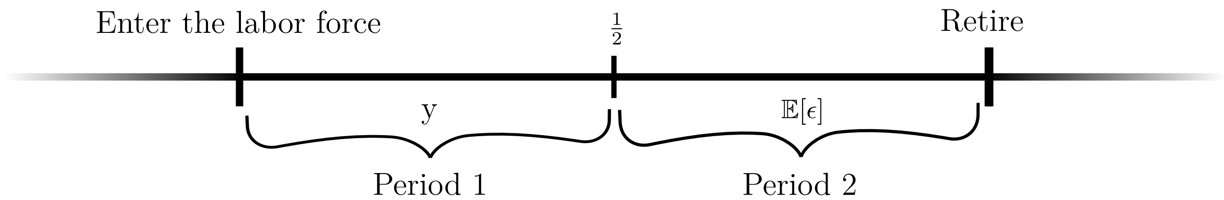
$$
\begin{aligned}
d^l: \qquad \frac{1}{y-d^l-m^l} &= \beta R^d \left[\frac{p^\epsilon}{R^d d^l + R^m m^l + s_{\max}} + \frac{1-p^\epsilon}{R^d d^l + s_{\min}}\right] \\
&\quad + \gamma \left[\frac{(R^d d^l)^{-\sigma}}{(R^d d^l)^{1-\sigma} + \lambda (R^m m^l)^{1-\sigma}}\right], \qquad (41) \\
m^l: \qquad \frac{1}{y-d^l-m^l} &= \beta R^m \left[\frac{p^\epsilon}{R^d d^l + R^m m^l + s_{\max}} + \frac{1-p^\epsilon}{R^d d^l + s_{\min}}\right] \\
&\quad + \gamma\lambda \left[\frac{(R^m m^l)^{-\sigma}}{(R^d d^l)^{1-\sigma} + \lambda (R^m m^l)^{1-\sigma}}\right]. \qquad (42)
\end{aligned}
$$

Since the equilibrium solutions cannot be found analytically, I solve the model numerically The gradient and the Hessian are provided by automatic differentiation.

5.3 Calibration

I calibrate the model over an agent's total working period of 40 years. Figure 9 shows the two-period economy. The first half is the first period where the household receives the endowment. The second period is the remaining half of the working life, in which the household experiences a stochastic income. Table 4 summarizes the baseline calibration.

Figure 9: Two-period economy



The endowment y is set to 1. The discount factor is set to $\beta = 0.82$ which implies an annual discount factor of approximately 0.99.

The risk-free return on deposits is set at the standard value of $R^d = 1/\beta$, matching an annual return of 1.01. As mentioned previously, I assume that CBDC pays a lower return than deposits, and set $R^m = 1.1$. For the calibration of risky asset returns and probabilities see Appendix C.

The liquidity service parameter γ is calibrated internally to 0.05 to match the empirical average deposit-to-consumption ratio. The relative liquidity benefit of CBDC is normalized to $\lambda = 1$. Finally, I set the inverse elasticity of substitution between CBDC and deposits, σ, to 1/3. This corresponds to a low degree of substitutability following Bacchetta and Perazzi (2022).

Table 4: Model Parameters

Parameter	Value	Source/Motivation
y	1	Assumption
β	0.82	Compounding the annual value of 0.99
R^d	$1/\beta$	Compounding the annual return of 1.01
R^m	1.1	Assumption ($R^m < R^d$)
$\bar{R}^a$	3.77	See Appendix C
$\underline{R}^a$	0.83	See Appendix C
p^a	0.92	See Appendix C
γ	0.05	Internally calibrated
λ	1	Assumption
σ	1/3	Bacchetta and Perazzi (2022)

The table reports the calibration over the period length. The two periods have the same duration.

5.4 Portfolio choices

This section examines how high- and low-financial literate agents allocate their portfolios in different economic environments.

5.4.1 Deterministic second-period income

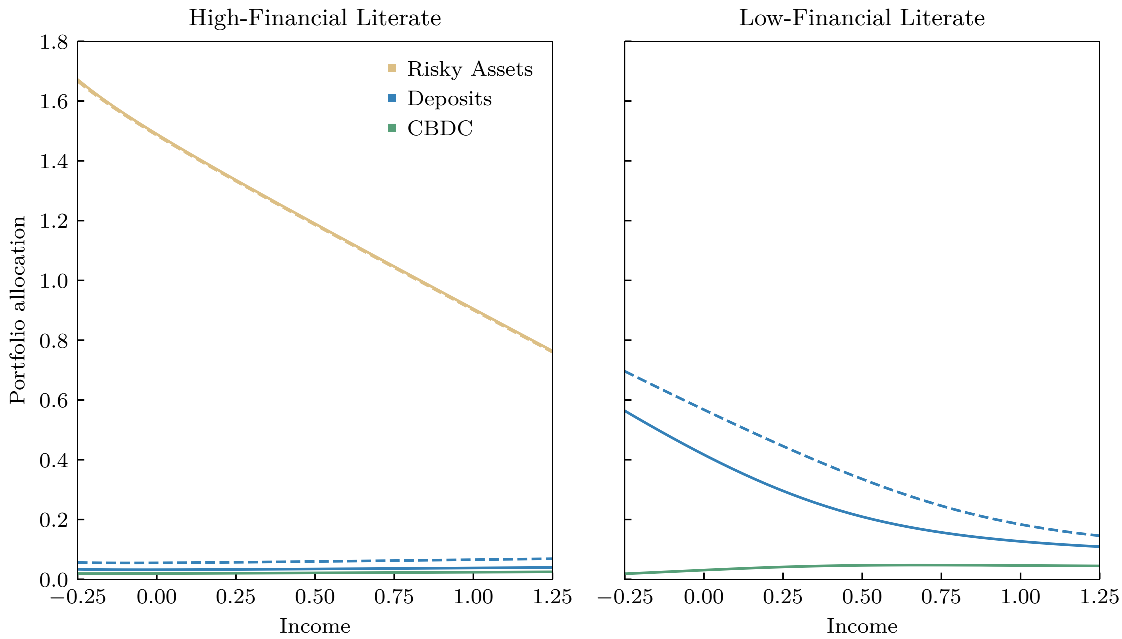
I start by analyzing the agents' portfolio decisions in the deterministic case when the maximum and minimum second-period incomes are equal, i.e., $s_{\max} \equiv s_{\min} = s$. Note that the HFL agent remains subject to stochastic returns on risky assets. Following the introduction of CBDC, portfolio allocation decisions adjust according to the relative attractiveness of the digital currency.

Figure 10 illustrates the portfolio allocation for high- and low-financial literacy agents in the second period. Dashed lines represents pre-CBDC allocations, while solid lines show allocations after CBDC introduction.

After the introduction of CBDC, the liquidity term in the agents' utility function depends on deposits and CBDC, as specified by equation (29). Assuming that agents perceives CBDC and deposits as equally useful for liquidity purposes, i.e., $\lambda = 1$, the optimal allocation of liquidity is an even split between deposits and CBDC in the limit where consumption needs are fully satisfied, i.e. $\gamma \to \infty$.

In scenarios where second-period income is significantly negative (i.e., a high cost), both agents respond by increasing their savings, achieved by reducing current consumption to

Figure 10: Portfolio allocation in deterministic scenario



This figure shows the portfolio allocation in the second period for high- and low-financial literate when the maximum and minimum second-period incomes are identical. Dashed lines represent pre-CBDC allocations, while solid lines show allocations after CBDC introduction.

ensure sufficient funds for second-period consumption. The HFL agent invests in risky assets, while the LFL agent can only save in deposits. After CBDC introduction, the LFL agent gains access to an additional saving device but continues to allocate mainly to deposits due to their higher return relative to CBDC.

For the HFL agent, the higher returns on risky assets result in greater total wealth in the second period, allowing them to meet both consumption and liquidity needs. After CBDC introduction, the HFL agent can achieve a liquidity allocation between CBDC and deposits across all income levels closer to the liquidity benefit term optimum. In contrast, the LFL agent, who cannot invest in risky assets, must rely on the higher-return saving option, i.e., deposits, to sustain their second-period consumption. Consequently, the LFL agent prioritizes deposits over CBDC, resulting in a portfolio that further diverges from the optimal liquidity allocation.

Despite the LFL agent's continued preference for deposits, they invest more in CBDC in absolute terms than the HFL agent. This pattern qualitatively aligns with my empirical findings, where low-financial literacy households show a greater probability to participate following the introduction of a new financial instrument than high-financial literacy households.[13] In the model, this difference arises because the HFL agent uses risky assets to hedge against negative incomes. Consequently, these distinct portfolio behaviors illustrate how financial literacy shapes not only access to assets but also the extent of participation in CBDC.

5.4.2 Stochastic second-period income

Next, I relax the assumption on the outcomes of the stochastic second-period income, allowing for the maximum and minimum income values to differ, i.e., $s_{\max} \neq s_{\min}$. Variation in second-period income introduces a common layer of uncertainty that affects agents' future resources, allowing me to investigate how agents with different levels of financial literacy adjust their portfolio choices, including CBDC demand, when facing such uncertainty. Specifically, I consider a maximum positive second-period income of $s_{\max} = 1.25$ and explore variation in the minimum income $s_{\min}$. As a reference, setting $s_{\min} = -0.25$ implies a coefficient of variation in the income distribution of approximately 1.5, matching the empirical coefficient of variation observed in earnings data.[14]

Figure 11 illustrates the second-period portfolio allocation for agents with high and low financial literacy. Dashed lines represents the pre-CBDC allocations, while solid lines show allocations following CBDC introduction.

To explore effects of income uncertainty, I vary the minimum income $s_{\min}$ while keeping the expected second-period income constant at $\mathbb{E}[\epsilon] = 1$ by adjusting the probability of positive income p^ϵ as follows:

$$p^\epsilon(s_{\min}) = \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}}. \tag{43}$$

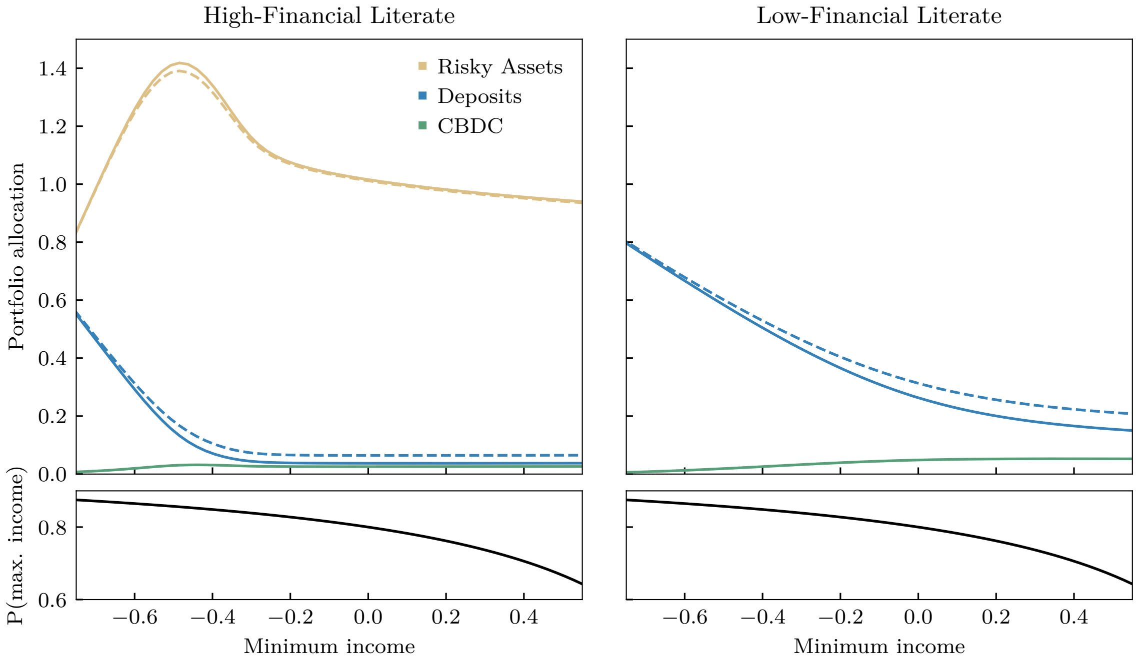
This approach allows me to analyze the effect of the uncertainty alone, as the expected income remains fixed, in contrast to the deterministic scenario in Figure 10. As the the minimum income becomes more negative, i.e., moving left in Figure 11, income variance increases, where the variance is

$$\text{Var}(\epsilon) = p^\epsilon s_{\max}^2 + (1 - p^\epsilon) s_{\min}^2 - \mathbb{E}^2[\epsilon]. \tag{44}$$

[13]The empirical analysis examines the extensive margin of participation following the introduction of the new financial instrument, while the theoretical model investigates agents' portfolio allocation decisions once the new instrument has been introduced.

[14]The coefficient of variation measures relative variability within a distribution, calculated as the ratio of the standard deviation to the mean.

Figure 11: Portfolio allocation with stochastic income



This figure shows the portfolio allocation in the second period for high- and low-financial literacy agents with stochastic income. The dashed lines represent pre-CBDC allocations, while solid lines show allocations after CBDC introduction. Variation results from adjusting the minimum income while holding expected income constant by adjusting the probability of positive income, as shown in the lower plot.

Substituting equation (43), income variance as a function of the minimum income becomes

$$\mathrm{Var}(\epsilon) = (s_{\max} - \mathbb{E}[\epsilon])^2 \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}} + (s_{\min} - \mathbb{E}[\epsilon])^2 \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}}. \tag{45}$$

Variance thus increases with more negative values of the minimum income and behaves quadratically for large negative values.

This income uncertainty, as in the deterministic scenario, leads to deviations from the optimal liquidity allocation. Note that the key determinant for agents' portfolio adjustments is not the mean or variance of income but rather the severity of the minimum income, i.e., the worst-case scenario agents may face. This is due to the presence of $s_{\min}$ in the constraints of equations (20), (26), (33), and (40). Agents ultimately reach a stable configuration for liquid asset allocation beyond a particular threshold for the minimum income, with HFL agents achieving stability at a less negative income level.

The hump-shaped response observed in risky asset allocation reflects their initial effectiveness as a hedge against moderate negative income scenarios. However, as the minimum income becomes more negative, a tipping point occurs where risk becomes too high, causing HFL agents to shift toward safer assets. This pattern is further supported by modeling slightly riskier asset, which flattens the hump, as shown in Figure 12 in Appendix D. Finally, as in the deterministic income scenario, the LFL agent holds more CBDC in absolute terms than the HFL agent.

6 Conclusion

Government policies have the potential to increase participation in financial markets, which is inefficiently low. This paper evaluated the effects of government policies targeted at households on market participation, considering the role of financial literacy, with a focus on the potential introduction of retail CBDC. By using the introduction of retail Treasury Bonds in Italy as a proxy for CBDC adoption, I provide insights into how financial literacy influences households' likelihood to engage with the new instrument.

The empirical findings revealed that financial literacy positively affected household likelihood to participate after the introduction of the new policy. Interestingly, the effect was non-monotonic, with households exhibiting a low level of financial literacy being more likely to participate compared to the financially illiterate and high-financial literate household groups. The results also suggested that households reallocated their portfolios following the new policy, shifting from other securities and stocks to Treasury Bonds, highlighting the key role of financial literacy in reshaping household investment behavior.

Building on these empirical insights, the theoretical model explored how financial literacy impacts CBDC demand through portfolio allocation decisions. In the deterministic income scenario, the model showed that the LFL agent held more CBDC in absolute terms than the HFL agent, who leveraged risky assets to hedge against negative income. This allocation pattern, similar to the empirical finding, underscored how low-financial literacy households may be more likely to participate in CBDC market. In the stochastic income scenario, uncertainty amplified these differences, with the worst-case income scenario driving significant portfolio adjustments. Here, HFL agents shifted away from risky assets to safer assets as uncertainty increased, highlighting the importance of income uncertainty in shaping portfolio allocation.

This paper offers valuable insights for policymakers. First, it highlights the importance of considering financial literacy when designing a CBDC. Since households with different levels of financial literacy respond differently to new financial instruments, clear communication of the benefits and functionality of CBDC is essential to ensure its adoption across a broad segment of the population. Second, the model provides insights into how different agents might reallocate their portfolios following the introduction of CBDC, depending on design features and the overall economic environment.

Future research could extend this work by using actual CBDC data when available, as well as further exploring the behavioral aspects of household financial decision-making in the context of new financial instruments. This would offer a richer understanding of the dynamics at play and provide more targeted recommendations for policy design.

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A Additional material

Table 5: Italian government securities

	BOTs	*CTZs*	*CCTs*	*BTPs*
Maturity	< 1 year	2 years	5-7 years	3-50 years
Coupon	Discount at issuance		Floating semi-annual	
Auction type	Competitive Yield	Discretional choice of price/quantity issued		

This table compares the different Italian government securities. *Buoni del Tesoro Ordinari (BOTs)* correspond to Treasury Bills, *Certificato di Credito del Tesoro (CCTs)* correspond to Treasury Certificates, *Certificato del Tesoro Zero-coupon (CTZs)* correspond to Zero-coupon Bonds, and *Buoni del Tesoro Poliennali (BTPs)* correspond to Treasury Bonds with long-term maturity.. All four securities have a minimum denomination of $1,000$ euros and are subject to a 12.5% tax rate.
Source: Italian Ministry of Economy and Finance.

Table 6: Correct responses to financial literacy questions

	2008	2010	2016	2020
Inflation	72.84	69.55	61.42	59.29
Risk diversification	26.47	20.79	51.62	54.51
Interests	-	-	50.12	49.59
Mortgages	65.97	58.38	-	-
Average	55.09	49.57	54.39	54.47

This table reports the aggregate percentage of correct responses to financial literacy questions. Notice that incorrect responses include "Don't know" and "No answer". The average refers to the average number of correct answers.
Source: SHIW.

A.1 SHIW Financial literacy questions

Financial literacy questions are asked in the 2006, 2008, 2010, 2016, and 2020 SHIW waves. The correct answer is highlighted among those proposed.

A.1.1 Interests

Suppose you put 100 *euros into a (no fee, tax-free) savings account with a guaranteed interest rate of* 2% *per year. You don't make any further payments into this account and you don't* *withdraw any money. How much would be in the account at the end of* 5 *years, once the interest payment is made?*[15]

1. *Less than* 102 *euro*
2. *Exactly* 102 *euro*
3. ***More than 102 euro***
4. *Don't know*
5. *No answer*

A.1.2 Inflation

Suppose you put 1,000 *euros into a (no fee, tax free) savings account with a guaranteed interest rate of 1% per year. Suppose furthermore inflation stays at* 2%. *In one year's time will you be able to buy the same amount of goods that you could buy by spending today* 1,000 *euros?*

1. *Yes*
2. ***No, less than I could buy today***
3. *No, more than I could buy today*
4. *Don't know*
5. *No answer*

A.1.3 Risk diversification

In your opinion, the purchase of shares of one company usually provides a safer return than buying shares of a wide range of companies through a mutual fund?[16]

1. *True*
2. ***False***
3. *Don't know*
4. *No answer*

[15] In the 2006 wave, the question is slightly different, considering an amount equal to 1,000 euros and 2 years. In this case, the answer "No answer" is not available.

[16] In the 2008 and 2010 waves, the question is formulated as: *Which of the following investment strategies do you think entails the greatest risk of losing your capital? (1)* ***Investing in the shares of a single company****, (2) Investing in the shares of more than one company, (3) Don't know, (4) No answer.* In the 2008 wave, the answer "No answer" is not available.

A.1.4 Mortgage

Which of the following types of mortgage do you think would allow you from the very start to fix the maximum amount and number of installments to be paid before the debt is extinguished?[17]

1. *Floating-rate mortgage*
2. ***Fixed-rate mortgage***
3. *Floating-rate mortgage with fixed installments*
4. *Don't know*
5. *No answer*

[17]In the 2006 and 2008 waves, the answer "No answer" is not available.

B Empirical results

Table 7: Logit estimation results

Dep. Var.: Market Participation	Treasury Bond		Other Govt. Bond		Stocks	
	(2)	(8)	(2)	(8)	(2)	(8)
$D^{12} \times LS^{10}$	0.16^{***}(0.05)		-0.21^{***}(0.04)		-0.06^{**}(0.02)	
$D^{12} \times LS^{10}_1$		0.60^{**}(0.26)		-0.25^{*}(0.13)		-0.24^{***}(0.09)
$D^{12} \times LS^{10}_2$		0.27^{**}(0.11)		-0.43^{***}(0.08)		-0.10^{*}(0.05)
LS^{10}_1	1.42^{***}(0.48)	1.16^{**}(0.52)	0.83^{***}(0.20)	0.84^{***}(0.21)	1.59^{***}(0.22)	1.67^{***}(0.23)
LS^{10}_2	1.98^{***}(0.46)	2.01^{***}(0.46)	1.12^{***}(0.19)	1.02^{***}(0.19)	1.92^{***}(0.21)	1.91^{***}(0.21)
Constant	-5.50^{***}(0.45)	-5.50^{***}(0.45)	-3.30^{***}(0.18)	-3.30^{***}(0.18)	-3.63^{***}(0.21)	-3.63^{***}(0.21)
Pseudo R^2	0.007	0.007	0.007	0.007	0.020	0.024

The table reports coefficient estimates using Generalized Estimating Equations (GEE), an extension of GLM for panel data. The sample counts a panel of 4,611 households over a two-year period. Robust standard errors in parentheses. Time-fixed effect included.
In (8), the baseline financial literacy level is 0. * p < 0.1; ** p < 0.05; *** p < 0.01

B.1 Robustness

Table 8: Logit estimation results with more levels of financial literacy

Dep. Var.: Market Participation	Treasury Bond		Other Govt. Bond		Stocks	
	(11)	(12)	(11)	(12)	(11)	(12)
$D^{12} \times LS^{10}$	0.15^{***}(0.05)		-0.20^{***}(0.03)		-0.05^{**}(0.02)	
$D^{12} \times LS_1^{10}$		0.60^{**}(0.26)		-0.25^{*}(0.13)		-0.24^{***}(0.09)
$D^{12} \times LS_2^{10}$		0.23^{*}(0.12)		-0.38^{***}(0.09)		-0.12^{**}(0.05)
$D^{12} \times LS_3^{10}$		0.47^{*}(0.26)		-0.59^{***}(0.18)		0.04 (0.16)
LS_1^{10}	1.43^{***}(0.49)	1.16^{**}(0.52)	0.82^{***}(0.20)	0.84^{***}(0.21)	1.59^{***}(0.22)	1.67^{***}(0.23)
LS_2^{10}	2.05^{***}(0.46)	2.09^{***}(0.46)	1.10^{***}(0.19)	1.09^{***}(0.19)	2.03^{***}(0.22)	2.04^{***}(0.22)
LS_3^{10}	1.64^{***}(0.51)	1.62^{***}(0.53)	1.23^{***}(0.21)	1.23^{***}(0.22)	1.39^{***}(0.24)	1.30^{***}(0.25)
Constant	-5.50^{***}(0.45)	-5.50^{***}(0.45)	-3.30^{***}(0.18)	-3.30^{***}(0.18)	-3.63^{***}(0.21)	-3.63^{***}(0.21)
Pseudo R^2	0.007	0.007	0.007	0.007	0.024	0.024

The table reports coefficient estimates using Generalized Estimating Equations (GEE), an extension of GLM for panel data. The sample counts a panel of 4,611 households over a two-year period. Robust standard errors in parentheses. Time-fixed effect included.
In (12), the baseline financial literacy level is 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

C Risky asset calibration

I calibrate risky-asset returns and probabilities using the binomial tree security pricing model [see, e.g., Petters and Dong (2016)].

I use market data for the annual returns on risky assets, considering a high return $\bar{r}^a = 1.09$ and a low return $\underline{r}^a = 0.6$. The high return reflects the average for best-performing assets in recent periods [Board of Governors of the Federal Reserve System (2021)]. The low return reflects the worst-case scenario where the agent exits the market at the lowest point of the Global Financial Crisis.

The probabilities for these returns are calibrated to match an annual equity premium of approximately 6% consistent with recent estimates [Damodaran (2024)]. The equity premium is defined as:

$$\text{Equity premium} = \mathbb{E}[r^a] - r^d, \tag{46}$$

where r^d is the annual risk-free return equal to 1.01. The stochastic returns on risky assets follow:

$$r^a = \begin{cases} \bar{r}^a = 1.09 & \text{with probability } f^a = 0.95, \\ \underline{r}^a = 0.6 & \text{with probability } 1 - f^a = 0.05. \end{cases} \tag{47}$$

Over the two periods of equal duration T years, the compounded risky asset returns follow a random multiplicative process:

$$R^a = \left\{ (\bar{r}^a)^{(T-n)} (\underline{r}^a)^n \quad \text{with probability } P = \binom{T}{n} (f^a)^{(T-n)} (1 - f^a)^n, \right. \tag{48}$$

where n represents the number of crisis years. For example, assuming a period duration of 20 years and considering probabilities as in equation (47), the case of one crisis year has a return on the risky assets equal to

$$R^a_1 = (1.09)^{19} (0.6)^1 = 3.08, \tag{49}$$

and happens with probability

$$P_1 = \binom{20}{1} (0.95)^{19} (0.05)^1 = 0.38. \tag{50}$$

The possible outcomes over the period are reported in Table (9).

Table 9: Stochastic risky asset return over the period

n	P_n	R^a_n
0	0.358	5.6
1	0.377	3.08
2	0.188	1.69
3	0.059	0.93
4	0.013	0.51
5	0.002	0.28
...	...	...

To simplify, I combine the outcomes into two events. A high return occurs with probability

$$p^a = P_0 + P_1 + P_2 = 0.92, \tag{51}$$

and a return of

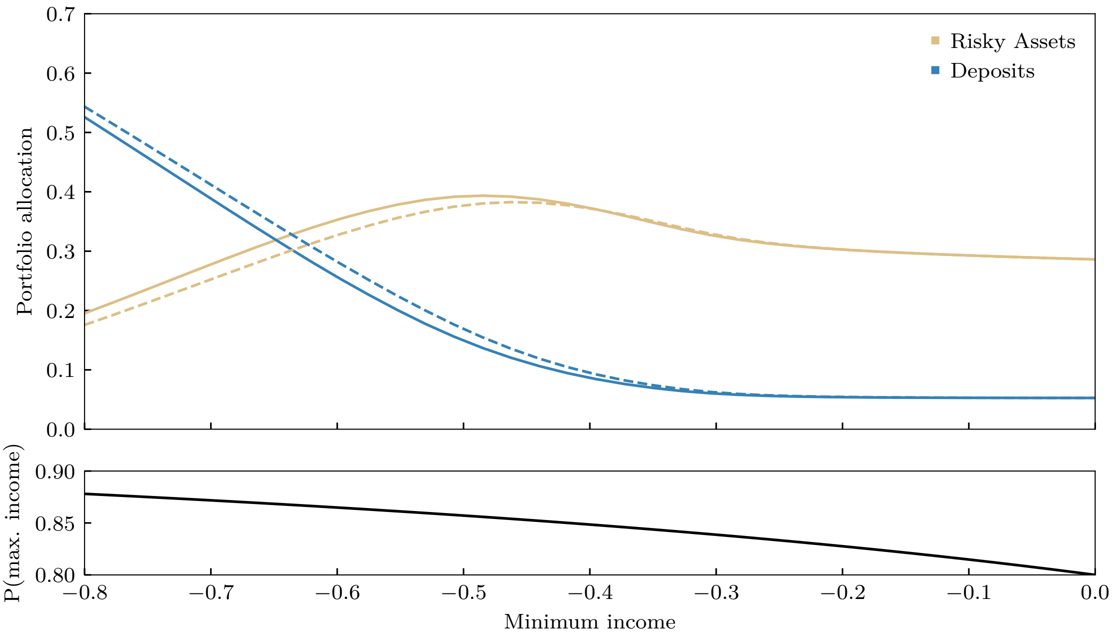
$$\bar{R}^a = \frac{P_0 R^a_0 + P_1 R^a_1 + P_2 R^a_2}{P_0 + P_1 + P_2} = 3.77. \tag{52}$$

A low return event occurs with a probability approximately equal to $(1 - p^a) = 0.08$ and a return of

$$\underline{R}^a = \frac{P_3 R^a_3 + P_4 R^a_4 + P_5 R^a_5}{P_3 + P_4 + P_5} = 0.83. \tag{53}$$

D Additional figures

Figure 12: Portfolio allocation with stochastic income



This figure shows the portfolio allocation in the second period for the high-financial literate agent with stochastic income. In the high-risk case, the value of minimum risky-asset return, $\underline{R}^a$, is reduced from 0.83 to 0.8. Note that the economy refers to the pre-CBDC economy.