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

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Abstract

This paper examines how household-targeted government policies influence financial market participation conditional on financial literacy, focusing on potential Central Bank Digital Currency (CBDC) adoption. Due to the lack of empirical CBDC data, 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 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, showing that households with some but low financial literacy are more likely to participate than other household groups. Based on these findings, I develop a theoretical model to explore the potential implications of financial literacy for CBDC adoption, showing that low-literate households with limited access to risky assets allocate more wealth to CBDC, while high-literate households use risky assets to safeguard against income risk. These results highlight the role of financial literacy 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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Non-Technical Summary

This paper investigates how household-targeted government policies affect market participation conditional on financial literacy and provides intuition on how demand for a Central Bank Digital Currency (CBDC) may vary across households. Central banks worldwide are still assessing whether and how to issue a CBDC — a digital form of central bank money. Given the lack of empirical CBDC data, I use a proxy policy to study how financial literacy affects households' likelihood of engaging with the new financial instrument.

The proxy is the introduction of retail Treasury bonds in Italy. While not perfectly equivalent, both instruments are government-backed and household-oriented. Retail Treasury bonds —– a subcategory of Treasury bonds exclusively issued to households — are investment instruments, whereas many central banks envisage CBDC as a means of payment. Here, CBDC is considered useful for transactional and store-of-value purposes, following Li (2023).

I use data from the Bank of Italy's Survey on Household Income and Wealth to empirically assess the impact of the first retail Treasury bond *Italia* on participation in the broader Treasury bond market. Introduced in March 2012 with yields indexed to domestic inflation, the Treasury bond *Italia* offered an ex-ante attractive investment compared to a comparable standard Treasury Bond, given positive inflation expectations. Results show that financial literacy increases the likelihood of participation after introducing the new instrument, but the effect is non-monotonic: households with some but low financial literacy are more likely to participate than financially illiterate and highly literate households. The findings also suggest a portfolio reallocation from other government securities and stocks toward Treasury bonds.

Building on these insights, I develop a simple two-period model with two types of agents differentiated by financial literacy, which determines access to risky investments. The high-literacy agent can invest in risky assets and risk-free deposits, while the low-literacy agent is limited to deposits. Agents live for two periods, receive an endowment in the first period, and an income in the second. They derive utility from consumption and value liquidity services from holding financial assets. In the economy with a retail CBDC, the low-literacy agent allocates more wealth to CBDC, irrespective of second-period income values. This reflects limited access to risky assets, while the high-literacy agent adjusts the portfolio by balancing risk and liquidity needs. When the second-period income is uncertain, differences between agents reduce: as uncertainty increases, the high-literacy agent shifts from risky assets toward safer options like CBDC.

Overall, the findings show that households with different levels of financial literacy respond differently to new financial instruments. For CBDC, clear communication of its benefits and functionality is essential to foster broad and inclusive adoption.

1 Introduction

It has been well-documented that household participation in financial markets is limited, resulting in potential welfare costs due to non-participation [Guiso and Sodini (2013), Haliassos (2021)]. 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 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), and Williamson (2022)], there is little evidence of the effects of introducing CBDC on market participation. This lack arises because central banks are still assessing whether and how to issue a CBDC, making it difficult to empirically investigate adoption patterns. Although everyone could access CBDC, the extent to which households will use it might differ based on personal characteristics and preferences. While CBDC would be relatively easy to use in principle, adoption may depend on individuals' understanding of its benefits and functionality, which is closely tied to their level of financial literacy.

This paper provides intuition on how CBDC demand might vary based on household characteristics. Specifically, it evaluates the effects of financial literacy on CBDC adoption. Given the lack of available empirical data on CBDC, I use a proxy to explore how financial literacy affects households' 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 are household-oriented. While retail Treasury bonds are investment instruments and many central banks envision CBDC primarily as a means of payment, I consider a CBDC useful for both transactional and store-of-value purposes, similar to Li (2023). In the theoretical framework, I model CBDC as interest-bearing but return-dominated by deposits. Although central banks are currently considering non-interest-bearing CBDC designs, I later show that the results are robust even in this case. All in all, while not a perfect substitute, retail Treasury bonds offer a suitable comparative proxy for studying CBDC adoption. Based on the empirical findings, I then develop a simple illustrative 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.

I empirically evaluate the effects of the introduction of retail Treasury bonds on household participation, conditional on financial literacy. 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).

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 with some but low financial literacy being more likely to participate following the introduction of the new instrument compared to the financially illiterate and highly 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 the potential implications of financial literacy for CBDC adoption. I use the empirical insights to inform the theoretical framework, which considers a simple two-period endowment economy with two types of agents, differentiated by their financial literacy, which determines access to risky investments. The high-financially literate agent can invest in risky assets and risk-free deposits, while the low-financially literate agent is limited to deposits. Each agent lives for two periods, receives an initial endowment in the first period, and an income in the second. Agents derive utility from consumption and value liquidity services from holding financial assets. The government introduces a CBDC

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

accessible to both types of agents, which is potentially interest-bearing and offers benefits relative to deposits.

The model examines how high- and low-financially literate agents allocate their portfolios in different economic environments. If second-period income is deterministic, the results reveal that low-financially literate households hold more CBDC than high-financially literate households, who rely on risky assets to safeguard against income risk, thereby reducing their need for CBDC. Introducing stochastic second-period income reduces these differences: As uncertainty rises, high-financially literate households reallocate away from risky assets toward safer options like CBDC. This analysis offers insights relevant to policymakers for designing an effective CBDC that can achieve 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 Nederlandsche 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 second IACOFI in 2020, 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, 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 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 eventual portfolio reallocation.

This paper also contributes 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. An exception is Li (2023) who 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 from the Netherlands, Bijlsma et al. (2023) 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 (POS) payments, examining how payment method attributes influence consumer choices. Similarly, Nocciola and Zamora-Pérez (2024) assess transactional demand for CBDC at the POS, 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) focus on the CBDC's role as a means of payment, this study considers a CBDC useful for both transactional and store-of-value purposes, similar 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 rest of the paper is organized as follows. Section 2 provides an overview of the Italian government bond market. Section 3 describes the data used in the empirical exercise. Section 4 presents the empirical analysis and its results. Section 5 describes the theoretical framework and portfolio choices following the CBDC introduction. Section 6 concludes.

2 Italian government bond market

This section outlines the Italian government bond market. The landscape of Italian government securities is diverse, with four broad categories available to private and institutional investors: Treasury bills, Zero-coupon bonds, Treasury certificates, and Treasury bonds.[2] 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, they represented 66.47% of the total Italian government securities market [MEF (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 in that they offer a final bonus to whoever purchases them during the placement period and holds them until maturity. Treasury bonds *Italia* have yields linked to the Italian Consumer Price Index, while Treasury bonds *Futura* and *Valore* provide 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.

The issuance of retail Treasury bonds is primarily driven by the government's financing needs and strategic debt management plans, rather than direct demand from retail investors. The government schedules retail Treasury bond offerings to align with its budgetary requirements and broader economic objectives. For example, the introduction of Treasury bonds *Futura* and *Valore* was part of efforts to support economic recovery and public debt management following the 2019 COVID crisis.

Retail Treasury bonds are allocated through a non-competitive subscription process during predefined offering periods, ensuring all valid orders are fully satisfied. The Italian Ministry of Economy and Finance (MEF) announces these offerings in advance and provides detailed terms and conditions to inform potential investors, while the bonds are issued via the MOT platform of the Milan Stock Exchange to guarantee broad accessibility for individual investors.

Since their introduction, retail Treasury bonds have received a positive response from retail investors. For instance, the most recent ones, *Valore*, saw a constant positive take-up since their 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 with 18.3

[2]Table A.1 in Appendix A summarizes the differences among government securities in terms of maturity, remuneration, and auction type.

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	No	Yes	Yes*	Yes

Note: This table compares the types of retail Treasury bonds among themselves and with the standard Treasury bonds. The standard Treasury bond yield refers to the year 2023 and represents the weighted average interest rate. All Treasury bonds have a minimum denomination of €1,000 and are subject to a 12.5% tax rate. * The *Futura* final bonus is linked to GDP.
Source: Italian Ministry of Economy and Finance.

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.[3] In February 2025, the Italian government introduced a new retail Treasury bond within the Valore family, called *BTP Più*. This bond has quarterly coupon payments and maintains the "step-up" mechanism but has a longer maturity of 8 years. Its innovation is the option for early redemption after 4 years: Investors who purchase the bond during the placement period and hold it until the exercise date in 2029 can redeem their principal, fully or partially, in increments of at least €1,000. Those who do not exercise this option will continue to receive step-up coupons and are guaranteed the full principal at maturity. The first issue of *BTP Più* raised approximately 15 billion euros, a couple of billion less than the record of Treasury bonds *Valore*, but four above the previous issue, with around 642,000 contracts [MEF (2025b)].

This analysis focuses on the introduction of the first retail Treasury bond *Italia*, whose first issuance was announced on March 16, 2012, and took place from March 19 to March 22, 2012. The announcement detailed the bond's characteristics, including its four-year maturity, guaranteed minimum real coupon rate of 2.25%, and semi-annual coupon payments linked to

[3]See MEF (2023a), MEF (2023b), and MEF (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.

the Italian Consumer Price Index [MEF (2012a)]. The standard Treasury bond with ISIN *IT0004805070*, issued in March 2012 with a three-year maturity, serves as a useful reference for comparing the first issuance of retail Treasury bonds *Italia*. This standard government bond offered a fixed coupon rate of 2.50%, providing semi-annual interest payments and predictable returns over its three-year maturity [MEF (2012b)]. Unlike Treasury bonds *Italia*, which are indexed to domestic inflation and designed specifically for retail investors, this bond was a conventional fixed-rate instrument targeting a broader investor base. Ex-ante, the first issuance of the retail Treasury bond *Italia* appeared to be an attractive investment, particularly for retail investors concerned about inflation risk. Given its inflation protection, guaranteed minimum return, principal revaluation, and final bonus, it likely presented a more attractive investment compared to the standard Treasury bond, particularly in light of the positive inflation expectations in 2012.

The inaugural introduction of retail Treasury bonds *Italia* received a positive response from retail investors, corresponding to about 7.3 billion euros with 133,479 contracts concluded [MEF (2012f)]. By the end of 2012, Treasury bonds *Italia* attracted a total of 27 billion euros over three issuances [MEF (2013)]. The contract size distribution confirms strong participation by small savers. Across all three issuances in 2012, more than 80% of contracts were below the 50,000–euro threshold typically used to distinguish retail from institutional investors. More than half of these contracts were even below 20,000 euros, demonstrating the large participation of small savers.[4]

In the empirical analysis, I examine the effects of introducing the first retail Treasury bonds *Italia* on participation in the broader 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. In May 2025, the Ministry of Economy and Finance announced a new issuance of Treasury bonds *Italia*, scheduled from May 27 to May 30. This new bond has a seven-year maturity and offers a final extra bonus of 1% to investors who purchase it during the placement period and hold it until maturity [MEF (2025c)]. The May 2025 issuance attracted over 8.79 billion euros, with 65% of subscriptions coming from individual investors and over 88% of contracts below 50,000 euros, confirming the continued strong interest among small savers [MEF (2025a)].

[4]See MEF (2012c), MEF (2012d), and MEF (2012e) for the details on the placement of the first three issuances of retail Treasury bonds *Italia*, respectively.

3 Survey data

To study the effects 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 in 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., ranking, 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 wave year. For example, the 2012 survey was administered in 2013. A typical question asked in the 2012 survey is

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, in the survey, real estate includes the sum of all real estate, such as the primary residence, secondary houses (potentially rented out), commercial buildings, and land. 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. Specifically, 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.

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

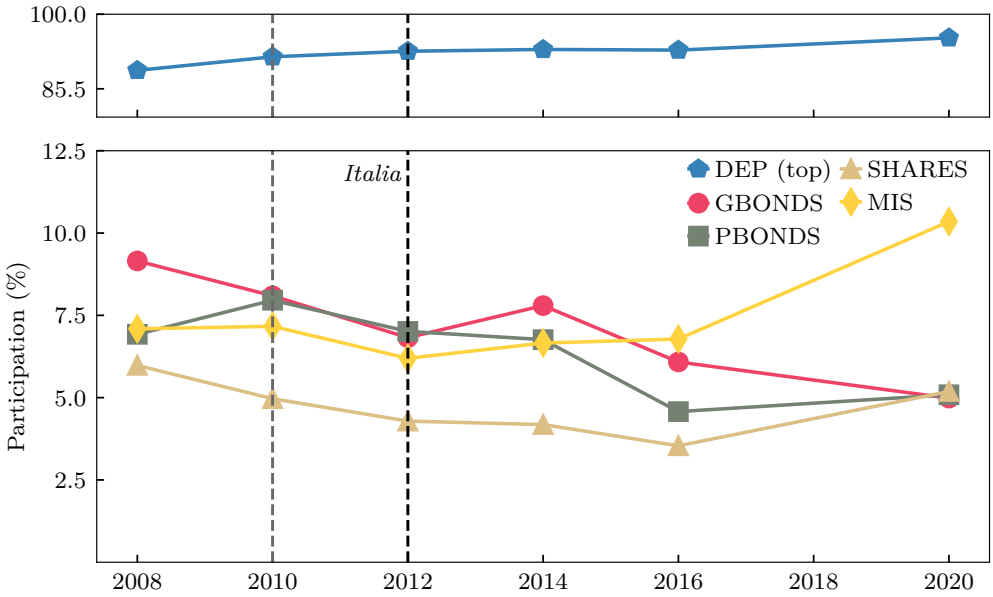
Note: This table details individual assets in SHIW, grouped in classes. *Buoni del Tesoro Ordinari (BOTs)* correspond to Treasury bills, *Certificato di Credito del Tesoro (CCTs)* correspond to Treasury certificates, *Certificato del Tesoro Zero-coupon (CTZs)* correspond to Zero-coupon bonds, and *Buoni del Tesoro Poliennali (BTPs)* correspond to Treasury bonds with long-term maturity.
The composition of 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.

Figure 1 illustrates the average market participation of Italian households in the waves from 2008 to 2020. Households show a significant preference for traditional financial assets, with

[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, and against accidents.

consistently high participation in deposits, which is reported in the top panel. Participation in government bonds shows a declining trend, falling from around 9% in 2008 to approximately 6% in 2020. Private bonds show a similar trend. 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 1: Market participation of Italian households

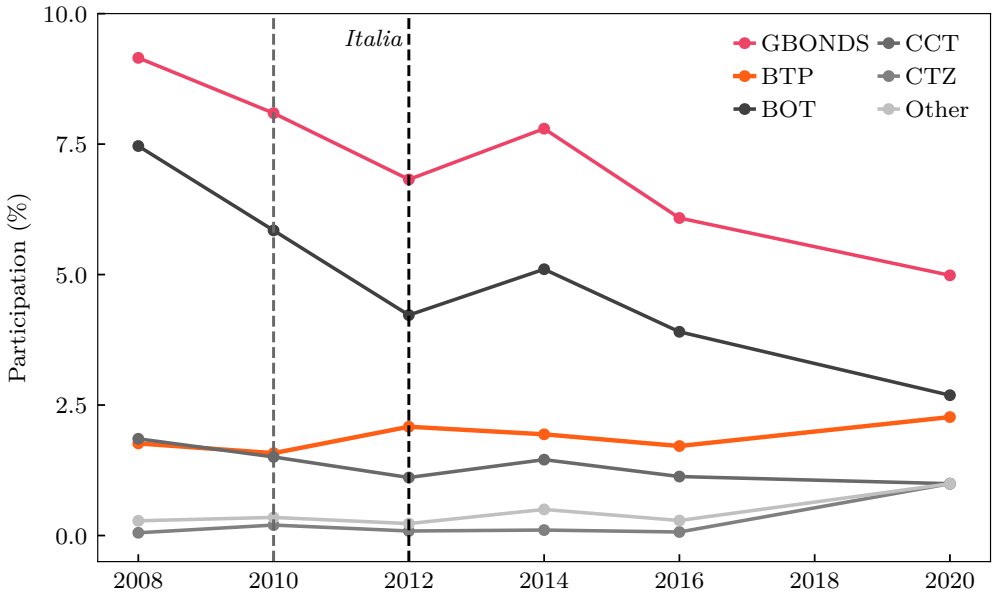


Note: This figure shows market participation across the sample of Italian households. Weighted average of the observations.
Source: SHIW and author calculations.

Figure 2 provides a detailed breakdown of participation in government securities. While Treasury bills (*BOTs*) exhibit strong participation throughout the sample, their trend is sharply declining. In contrast, participation in Treasury bonds (*BTPs*) remains low but relatively stable, with a slight upward trend. Participation in other government securities is lower across the entire sample period. The two vertical lines in Figure 2 mark the 2010 wave preceding the policy introduction and the 2012 wave when the policy was implemented. Notably, participation in the Treasury bond market increases between these two waves, possibly reflecting the impact of the introduction of retail Treasury bonds *Italia* in 2012.[6]

[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 2: Government securities participation of Italian households



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

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.

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. To evaluate the reliability of each component, the authors use the Cronbach coefficient, which assesses internal coherence of the different items that make up each component: The higher the correlation among items and the greater their number, the higher the coefficient. 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, the 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, asked in the last two waves, shows correct response rates of around 50%. 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.[9]

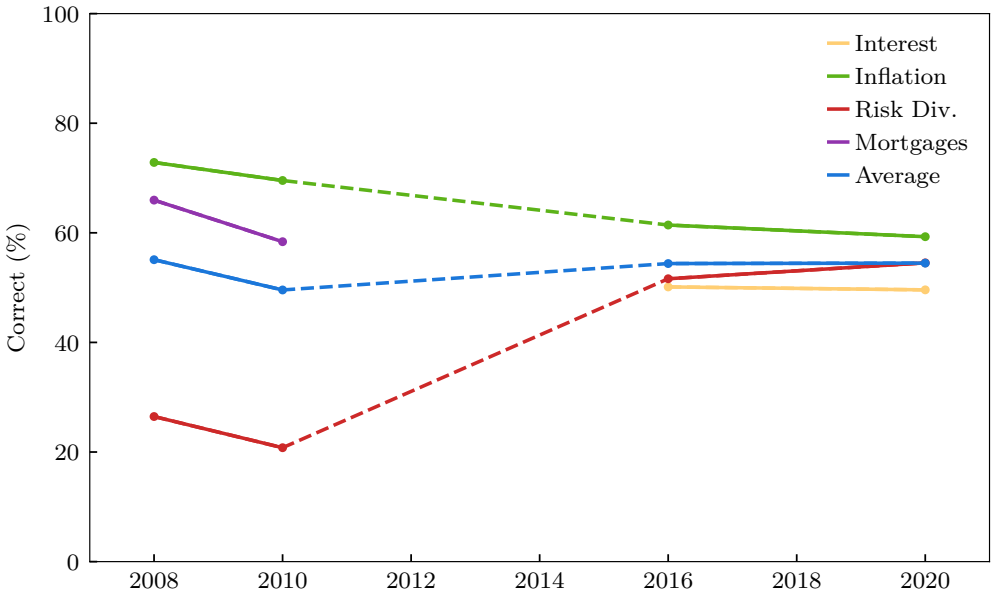
Similar to Figures 1 and 2 in Section 3.1, Figures 4 and 5 report overall market participation and participation in government securities, respectively, distinguishing between financial literacy score levels. Figure 4 suggests that households with higher financial literacy scores

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

[8] See Table A.2 in Appendix A for the percentage numbers of correct responses.

[9] See Appendix A.2 for descriptive statistics for the financial literacy score by demographics, across Italian regions, and wealth distribution.

Figure 3: Correct responses to financial literacy question



Note: 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 and author calculations.

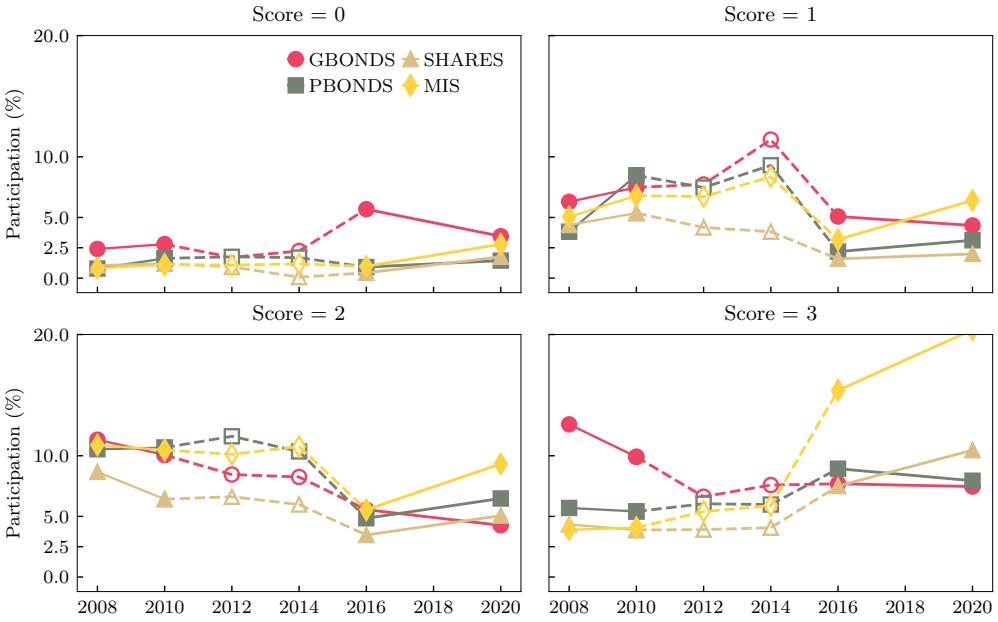
tend to hold more diversified portfolios. However, in the 2012 wave, households with the highest score level 3 appear less diversified than those with levels 1 and 2. A similar pattern emerges in Figure 5, which shows the breakdown by government securities. Focusing on the Treasury bond (*BTP*) market, 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 four waves since 2008, excluding 2012 and 2014 when the financial literacy questions were not included. Over time, the distribution becomes more evenly spread across financial literacy levels.

4 Retail Treasury bonds and market participation

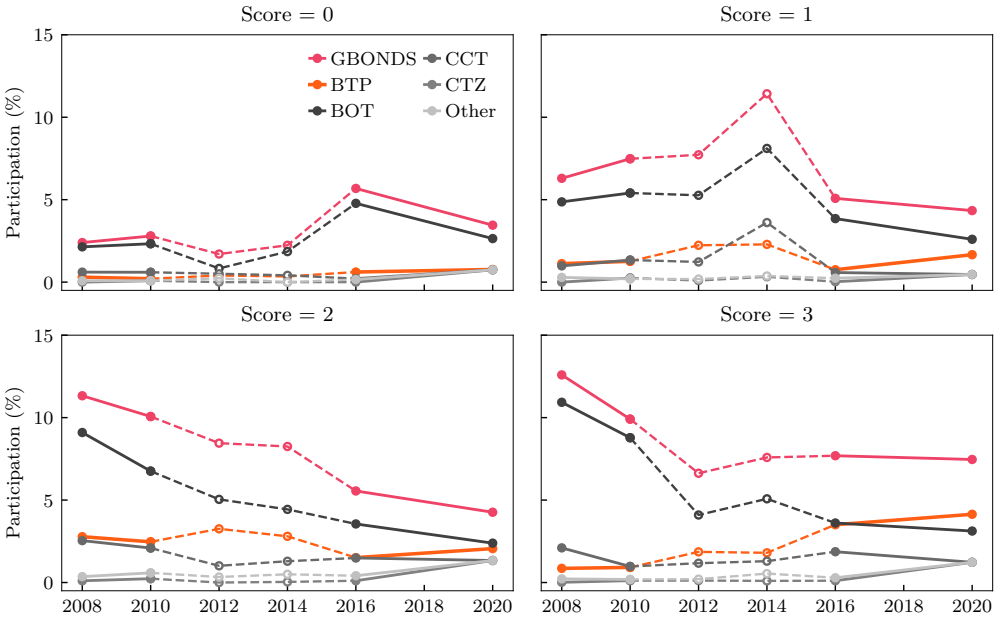
This section evaluates the effect of the introduction of retail Treasury bonds on household participation in the broader Treasury bond market. Previous studies have shown that financial literacy influences household financial behavior [see, e.g., Arrondel et al. (2016), van Rooij, Lusardi, and Alessie (2011), and Chen, Dai, and Guo (2023)]. The empirical model estimates the impact of the policy on participation across households with different levels of financial literacy, thereby quantifying the differential policy-financial literacy effect.

Figure 4: Market participation by literacy score level



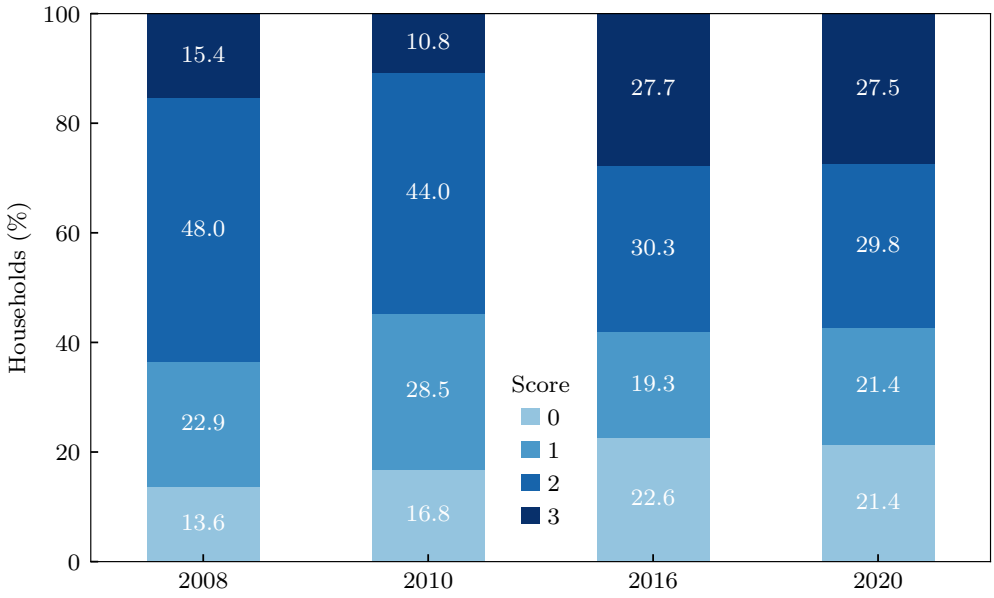
Note: This figure shows market participation across the sample of Italian households, distinguishing between financial literacy score levels. When the information on household literacy scores is missing for a specific year, the last data available are used. Weighted average of the observations. Deposits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

Figure 5: Government securities participation by literacy score level



Note: 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 and author calculations.

Figure 6: Percentage of households by financial literacy score level



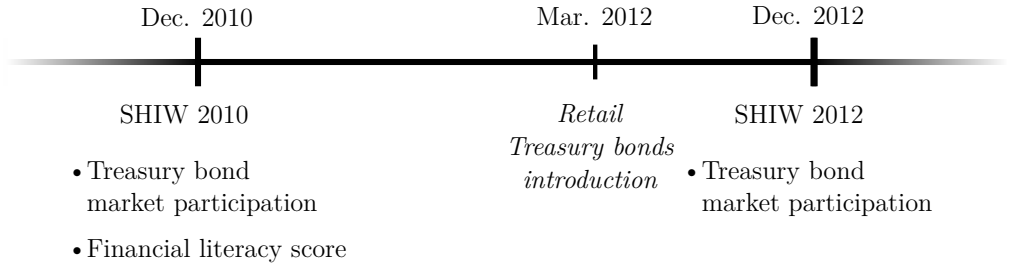
Note: This figure shows the percentage of households by financial literacy score level.
Source: SHIW and author calculations.

The policy 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 retail government policy on market participation can be seen right after their introduction. To purchase retail Treasury bonds, an individual must have an investment account with a bank or financial institution. Before opening an investment account, banks in Italy are required to assess the individual's financial knowledge and experience. This is typically done through a profiling questionnaire as part of the Markets in Financial Instruments Directive regulations. This questionnaire aims to evaluate the individual's understanding of financial products and ensure that the bank offers suitable investments based on the client's risk tolerance and knowledge. However, the questions in the questionnaire are not directly comparable to the "Big Three" questions commonly used to assess financial literacy, as they focus less on basic financial concepts and more on practical aspects related to investment behavior.

The financial literacy score defined in Section 3.2 can take four levels, each identifying a distinct household type: 0 for financially illiterate, 1 for low-financially literate, 2 for high-financially literate, and 3 for financially expert. 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. A traditional empirical challenge is 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.

Figure 7: Timeline of the short-run analysis



4.1 Baseline regression

I construct the empirical model using the Generalized Linear Model (GLM) framework, which extends linear regression to binary outcomes.[10] 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 $P_{it} = \mathbb{E}[y_{it}]$ represents 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:

$$z_{it} = \alpha + \beta(D_t^{12} \times LS_i^{10}) + \sum_{\ell=1}^{3} \gamma_\ell LS_{i\ell}^{10} + \boldsymbol{\eta}^\intercal \boldsymbol{X}_{it} + \epsilon_{it}, \quad t = 2010, 2012, \tag{2}$$

[10]Instead, using a Linear Probability Model (LPM) can produce biased estimates and inaccurate standard errors with binary outcomes and skewed distributions (such as the low initial share of Treasury bond investors), as the LPM's assumptions of homoscedasticity and normally distributed residuals do not hold for binary data.

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 four values corresponding to the same number of household types: 0 if financially illiterate, 1 if low-financially literate, 2 if high-financially literate, and 3 if financially expert.

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. Additionally, the coefficient vector $\boldsymbol{\eta}$ captures the effects of the vector of controls $\boldsymbol{X}_{it}$, which includes household demographic characteristics (age, age squared, a dummy for being married, and a dummy for being female), and an indicator of high risk aversion measured in 2010.

The estimated coefficient of interest, $\hat{\beta}$, can be interpreted through the odds ratio:[11]

$$\frac{P_1}{1-P_1} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}). \tag{3}$$

For the high-financially literate household (i.e., when $D^{12} \times LS^{10} = 2$), the odds ratio can be evaluated as:

$$\frac{P_2}{1-P_2} = \frac{P_1}{1-P_1} \times \exp(\hat{\beta}) = \frac{P_0}{1-P_0} \times \exp(2\hat{\beta}), \tag{4}$$

where $\exp(\hat{\beta})$ represents the multiplicative change in the odds (i.e., the odds ratio) for each one-unit increase in the policy-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 broader 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

$$z_{it} = \alpha + \sum_{\ell=1}^{3} \beta_\ell (D_t^{12} \times LS_{i\ell}^{10}) + \sum_{\ell=1}^{3} \gamma_\ell LS_{i\ell}^{10} + \boldsymbol{\eta}^\intercal \boldsymbol{X}_{it} + \epsilon_{it}, \quad t = 2010, 2012, \tag{5}$$

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.

[11] The odds of an outcome occurring is the ratio of successes to failures. See Appendix B.1 for the intuition for interpreting the estimated coefficient of interest.

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

$$\frac{P_\ell}{1-P_\ell} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}_\ell), \quad \ell = 1, 2, 3. \tag{6}$$

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

$$\frac{P_2}{1-P_2} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}_2). \tag{7}$$

The intuition is analogous to before: Following the introduction of retail Treasury bonds, the odds of a high-financially literate household participating in the Treasury bond market are $\exp(\hat{\beta}_2)$ 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.[12]

4.3 Results

Table 3 reports the estimated differential changes in the odds of participating. Recall that the linear baseline specification (2) uses financial literacy score levels for illiterate, low-literate, high-literate, and expert. 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 15%, as reported in column (1).[13] When considering alternative market participation dependent variables, column (3) shows that 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, as reported in column (5).

When considering the breakdown by financial literacy score level in the data, Treasury bond market participation rates at the end of 2010 were 0.21%, 1.26%, 2.47%, and 0.92% for financially illiterate, low-financially literate, high-financially literate, and financially expert, respectively. The results from the non-linear specification (5) suggest that, after the new

[12] I define stock holdings as holding either shares or managed investment schemes, as specified in Table 2, following Calvet, Campbell, and Sodini (2009), to capture direct and indirect equity market participation.

[13] Table B.1 in Appendix B reports the logit regression estimation results. Recall that the odds of participating change by, e.g., $\exp(\hat{\beta}) - 1 = \exp(0.14) - 1 = 15\%$.

instrument introduction, as literacy increases, the odds of participating in the Treasury bonds market also increase compared to the baseline for the financially illiterate. However, the rate of increase is not monotone across financial literacy levels, as indicated by the coefficients of low and high literacy in column (2) in Table 3: While for the low-financially literate, the odds of participating in the Treasury bond market increase by 80% compared to the financially illiterate, the increase is only 25% for the high-financially literate (57% for the financially expert). Similarly, the decrease in the odds of stock holdings, compared to the baseline of illiterate, is more pronounced for the low-literate, as illustrated in column (6). In contrast, column (4) shows that the decrease is greater for the highly literate and expert when considering participation in the market for other government securities.

Table 3: Changes in the odds of participation

Dep. Var.: Market Participation	Treasury bond		Other Govt. Bond		Stocks	
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{12} \times LS^{10}$	0.15^{***}		-0.19^{***}		-0.05^{**}	
$D^{12} \times LS_1^{10}$		0.80^{**}		-0.24^{**}		-0.21^{***}
$D^{12} \times LS_2^{10}$		0.25^{*}		-0.34^{***}		-0.12^{**}
$D^{12} \times LS_3^{10}$		0.57^{*}		-0.47^{***}		0.05
Test of $H_0 : \hat{\beta}_1 \leq \hat{\beta}_2$	$\hat{\beta}_1 = 0.80$, $\hat{\beta}_2 = 0.25$, p-value = 0.09					

Note: This 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. All regressions include a vector of baseline demographic controls and a dummy for high risk aversion in 2010.
Columns (1), (3), and (5) refer to specification (2), while columns (2), (4), and (6) refer to specification (5). In specification (5), the baseline financial literacy level is 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Test of $H_0 : \hat{\beta}_1 \leq \hat{\beta}_2$ for low- vs. high-literate households in Column (2) results in one-sided p-value = 0.09.

I formally test whether the effect on Treasury bond market participation for low-financially literate households exceeds that for the high-literacy group (i.e., compare the coefficients in the second and third row in column (2) in Table 3). Let $\delta = \beta_1 - \beta_2$ represent the difference in the respective model coefficients for the low- and high-literacy households from the fitted logistic model. I set up a one-sided hypothesis

$$H_0 : \delta \leq 0 \quad \text{vs.} \quad H_1 : \delta > 0.$$

Under the null hypothesis, the effect of the low-literate is at most equal to (or possibly less than) that of the high-literate. The alternative hypothesis states that low literacy has a larger effect.

To test this, one typically uses a Wald-type z-statistic rooted in large-sample theory. Concretely, after estimating the model's coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$, I compute $\hat{\delta} = \hat{\beta}_1 - \hat{\beta}_2$ and obtain its estimated variance from the model's covariance matrix. Because quasi-likelihood estimators (as in the case of Generalized Estimating Equations, an extension of GLM for panel data used here) are asymptotically normal under standard regularity conditions (e.g., correct mean specification, no perfect separation, sufficiently large sample), the ratio $r = \hat{\delta} \Big/ \sqrt{\mathrm{Var}(\hat{\delta})}$ serves as the test statistic and behaves approximately as a standard normal random variable for large samples. For a one-sided test, the p-value is $p = 1 - \phi(r)$, where $\phi(\cdot)$ is the standard normal cumulative distribution function. A sufficiently small p-value leads to rejecting H_0 and concluding that the evidence supports $\beta_1 > \beta_2$. The test rejects H_0 at the 10% significance level, confirming that the estimated coefficient of low-literacy households is statistically larger than that of high-literacy households.

To summarize, from the baseline linear regression (2), I find that financial literacy positively influenced participation in the broader 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 (5). From column (2) in Table 3, the low-financially literate households are more likely to participate 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 column (6) in Table 3, following the new policy, high-financially literate households are less likely to decrease participation in the stock market compared to the other household groups.

5 A simple two-agent endowment economy

This section explores the potential implications of financial literacy for CBDC adoption. While CBDC could be accessible to everyone, its adoption depends on several factors, including household financial literacy.

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 on the government and are household-oriented, making retail Treasury bonds a suitable comparative instrument for a CBDC. Findings from the retail Treasury bonds exercise in Section 4 suggest a differential financial behavior depending 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-financially literate household groups.

Building on these empirical insights, I develop a simple illustrative model to explore 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, high or low. For simplicity, I also abstract from modeling the financially expert group as separate from the high-literacy group, as their financial behavior does not differ significantly in the data.

The economy is populated by two types of agents differentiated by their financial literacy: high-financially literate (HFL) and low-financially 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 agents' investment opportunities is motivated by the SHIW data. Figure 8 shows the portfolio composition across the average sample of Italian households, distinguishing between high and low financial literacy groups. 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 incorporate this aspect, in the model I consider the limit scenario where the LFL agent does 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 receive income ϵ such that

$$\epsilon = \begin{cases} s_{\max} & \text{with probability } p^{\epsilon}, \\ s_{\min} & \text{with probability } 1 - p^{\epsilon}. \end{cases} \tag{8}$$

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

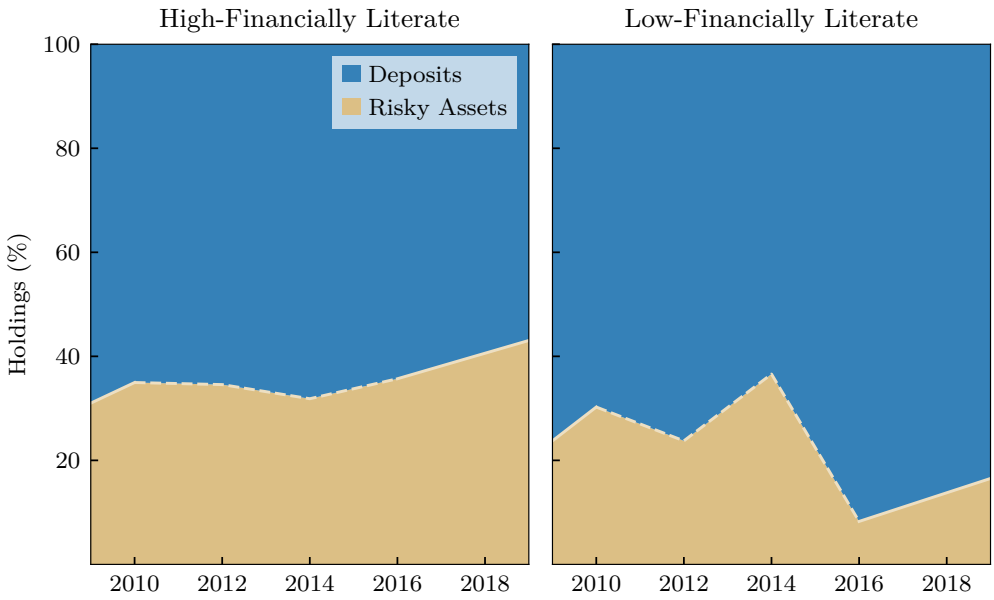
Agents maximize their discounted expected lifetime utility, $\mathbb{E}[\mathscr{U}]$, subject to budget constraints for each period. Each agent values liquidity services derived from holding financial assets and has a concave, additively separable utility function in consumption.

5.1 Pre-CBDC economy

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

$$\mathbb{E}[\mathscr{U}^j] = \ln(c_1^j) + \beta \mathbb{E} \ln(c_2^j) + \gamma \ln\Big(z(d^j)\Big), \quad j = h, l, \tag{9}$$

Figure 8: Portfolio composition across Italian households



Note: This figure shows the overall portfolio allocation across a sample of Italian households, distinguishing between high and low literacy groups. High-financially literate corresponds to households with literacy score levels 2 and 3, and low-financially literate to households with literacy score level 1. Risky assets include shares and managed investment schemes [Calvet, Campbell, and Sodini (2009)]. 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 and author calculations.

where j denotes the agent type h or l for the high- and low-financially literate agent, respectively; c_1^j and c_2^j are consumption in 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 $\gamma \geq 0$ the liquidity preference parameter, and liquidity services z a function of deposits d^j:

$$z(d^j) = d^j, \quad j = h, l. \tag{10}$$

The HFL agent can invest in risk-free deposits with return $R^d > 1$ and risky assets a with stochastic return R^a such that

$$R^a = \begin{cases} \bar{R}^a > R^d & \text{with probability } p^a, \\ \underline{R}^a < 1 & \text{with probability } 1 - p^a, \end{cases} \tag{11}$$

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:

$$c_1^h + a + d^h = y, \tag{12}$$

$$c_2^h = R^a a + R^d d^h + \epsilon. \tag{13}$$

The HFL agent maximizes the discounted expected lifetime utility

$$\begin{aligned} \mathbb{E}[\mathcal{U}^h] = \ln(y - a - d^h) + \beta \Big\{ & p^a \left[p^\epsilon \ln(\bar{R}^a a + R^d d^h + s_{\max}) \right. \\ & \left. + (1 - p^\epsilon) \ln(\bar{R}^a a + R^d d^h + s_{\min}) \right] \\ & + (1 - p^a) \left[p^\epsilon \ln(\underline{R}^a a + R^d d^h + s_{\max}) \right. \\ & \left. + (1 - p^\epsilon) \ln(\underline{R}^a a + R^d d^h + s_{\min}) \right] \Big\} \\ & + \gamma \ln(d^h), \end{aligned} \tag{14}$$

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

$$\underline{R}^a a + R^d d^h + s_{\min} > 0\,. \tag{15}$$

This mathematical constraint reflects the need of the agent to safeguard against the worst-case scenario of a negative return on the risky asset investment combined with a low minimum

income in the second period, regardless of the probability of this event.

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

$$c_1^l + d^l = y, \tag{16}$$

$$c_2^l = R^d d^l + \epsilon. \tag{17}$$

The LFL agent maximizes the discounted expected lifetime utility

$$\mathbb{E}[\mathscr{U}^l] = \ln(y - d^l) + \beta \left[p^\epsilon \ln(R^d d^l + s_{\max}) + (1 - p^\epsilon) \ln(R^d d^l + s_{\min}) \right] + \gamma \ln(d^l), \tag{18}$$

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

$$R^d d^l + s_{\min} > 0\,. \tag{19}$$

5.2 CBDC economy

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

$$\mathbb{E}[R^a] > R^d \geq R^m > 1, \tag{20}$$

such that the expected return on risky assets, $\mathbb{E}[R^a]$, 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:

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

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

$$z(d^j, m^j) = \left[(d^j)^{1-\sigma} + \lambda (m^j)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{21}$$

In equation (21), CBDC and deposits are imperfect substitutes, with $\sigma \geq 0$ representing the

inverse elasticity of substitution between the two liquid assets.[14] The parameter $\lambda \geq 0$ indexes the agent's preference for CBDC relative to deposits, reflecting factors such as liquidity benefit, privacy, or convenience of use.

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

$$c_1^h + a + d^h + m^h = y, \tag{22}$$

$$c_2^h = R^a a + R^d d^h + R^m m^h + \epsilon. \tag{23}$$

The HFL agent maximizes the discounted expected lifetime utility

$$\begin{aligned}\mathbb{E}[\mathscr{U}^h] = \ln(y - a - d^h - m^h) + \beta \Bigg\{ & p^a \left[p^\epsilon \ln(\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}) \right. \\ & \left. + (1-p^\epsilon) \ln(\bar{R}^a a + R^d d^h + R^h m^h + s_{\min}) \right] \\ & + (1-p^a) \left[p^\epsilon \ln(\underline{R}^a a + R^d d^h + R^m m^h + s_{\max}) \right. \\ & \left. \left. + (1-p^\epsilon) \ln(\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}) \right] \right\} \\ & + \gamma \ln\Big(z(d^h, m^h)\Big),\end{aligned} \tag{24}$$

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

$$\underline{R}^a a + R^d d^h + R^m m^h + s_{\min} > 0\,. \tag{25}$$

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

$$c_1^l + d^l + m^l = y, \tag{26}$$

$$c_2^l = R^d d^l + R^m m^l + \epsilon. \tag{27}$$

The LFL agent maximizes the discounted expected lifetime utility

$$\begin{aligned}\mathbb{E}[\mathscr{U}^l] = \ln(y - d^l - m^l) + \beta & \left[p^\epsilon \ln(R^d d^l + R^m m^l + s_{\max}) \right. \\ & \left. + (1-p^\epsilon) \ln(R^d d^l + R^m m^l + s_{\min}) \right] \\ & + \gamma \ln\Big(z(d^l, m^l)\Big),\end{aligned} \tag{28}$$

[14] 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)].

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

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

$$R^d d^l + R^m m^l + s_{\min} > 0\,. \tag{29}$$

Appendix C.1 reports the derived optimality conditions for HFL and LFL agents in the two economies, equations (C1)-(C8). Since the equilibrium solutions cannot be derived analytically, I solve the model through numerical optimization where the gradient and the Hessian are provided by automatic differentiation. However, certain limits can still be explored analytically.

For instance, the optimal allocation from a pure liquidity perspective can be derived by combining the first-order conditions for deposits and CBDC in the CBDC economy. I use the conditions for the LFL agent. Using the corresponding conditions from the HFL agent's problem and following the same steps yields identical results.

Taking the difference between the first-order conditions for CBDC and deposits gives:[15]

$$0 = \beta(R^d - R^m)\mathscr{B} + \gamma\left[\frac{(d^l)^{-\sigma}}{(d^l)^{1-\sigma} + \lambda(m^l)^{1-\sigma}} - \lambda\frac{(m^l)^{-\sigma}}{(d^l)^{1-\sigma} + \lambda(m^l)^{1-\sigma}}\right], \tag{30}$$

where

$$\mathscr{B} = \frac{p^\epsilon}{R^d d^l + R^m m^l + s_{\max}} + \frac{1 - p^\epsilon}{R^d d^l + s_{\min}}.$$

Rearranging gives

$$-\frac{\beta}{\gamma}(R^d - R^m)\mathscr{B} = \frac{(d^l)^{-\sigma} - \lambda(m^l)^{-\sigma}}{(d^l)^{1-\sigma} + \lambda(m^l)^{1-\sigma}}. \tag{31}$$

By taking the limit of the liquidity preference parameter $\gamma \to \infty$, the left-hand side of equation (31) vanishes. This implies that the numerator on the right-hand side must also vanish:

$$(d^l)^{-\sigma} = \lambda(m^l)^{-\sigma}. \tag{32}$$

Rearranging, the following condition is derived:

$$\frac{m^l}{d^l} = \lambda^{\frac{1}{\sigma}}. \tag{33}$$

This ratio between CBDC and deposits represents the allocation agents approach when considering just their liquidity needs (i.e., in the $\gamma \to \infty$ limit), and represents the upper

[15] See Appendix C.1 for details.

limit of CBDC holdings.

5.3 Calibration

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

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 $R^d = 1/\beta$, approximately equal to 1.22, and matching an annual return of 1.01. As mentioned previously, I assume that CBDC pays a lower return than deposits, and set $R^m = 1.10$, implying an annual return of 1.0048. The calibration of risky asset returns and probabilities uses the binomial tree security pricing model [see, e.g., Petters and Dong (2016)]. The high return on risky assets is set to 3.77 with a probability of 0.92, and the low return is 0.83 with complementary probability. See Appendix C.2 for details.

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

Table 4: Model parameters

Parameter	Value	Source/Motivation	Description
y	1	Assumption	Initial endowment
β	0.82	Compound. Annual value 0.99	Discount factor
R^d	1.22	Compound. Annual return 1.01	Deposits return
R^m	1.10	Assumption ($R^m < R^d$)	CBDC return
$\bar{R}^a$	3.77	See Appendix C.2	High risky assets return
$\underline{R}^a$	0.83	See Appendix C.2	Low risky assets return
p^a	0.92	See Appendix C.2	Probability of high return
γ	0.05	Internally calibrated	Liquidity service parameter
λ	1	Assumption (= to deposits)	CBDC benefit
σ	1/3	Bacchetta and Perazzi (2022)	Inv. elasticity of substitution

Note: This table reports the calibration over the period length of 20 years.

5.4 Portfolio choices

This section examines how high- and low-financially literate agents allocate their portfolios in different economic environments. Specifically, I study portfolio reallocation in the CBDC economy. Recall that after the introduction of CBDC, the liquidity term in the agents' utility function depends on deposits and CBDC, as specified by equation (21).

From equation (33), using the calibrated value for equal benefits for CBDC and deposits (i.e., $\lambda = 1$), the optimal allocation of CBDC relative to the total of liquid assets is

$$\frac{m^j}{d^j + m^j} = 50\%. \tag{34}$$

This value, derived from a pure liquidity perspective, represents the upper limit for CBDC allocation and provides a useful benchmark for analyzing portfolio allocation decisions under both deterministic and stochastic second-period income scenarios.

5.4.1 Deterministic second-period income

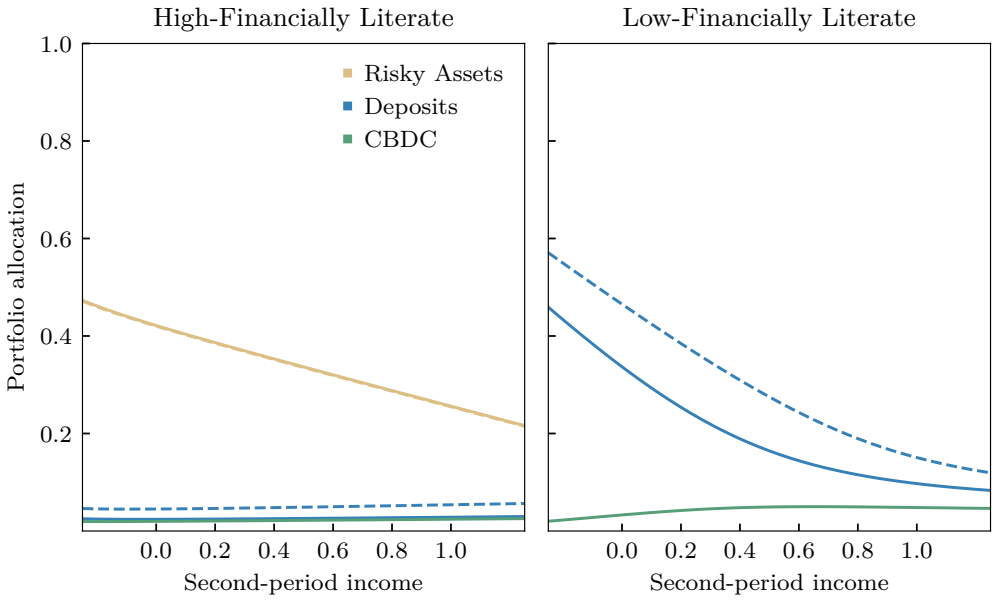
I start by analyzing the agents' portfolio decisions in the deterministic case when the maximum and minimum second-period incomes are equal, i.e., $s_{\max} = s_{\min} \equiv s$. Note that the HFL agent remains subject to stochastic returns on risky assets. Following the introduction of CBDC, portfolio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

Figure 9 illustrates how agents allocate their initial endowment, $y = 1$, in their portfolios as a function of second-period income values. Dashed lines represent pre-CBDC allocations, while solid lines show allocations after CBDC introduction.

In scenarios where second-period income is significantly low or even negative, both agents respond by increasing their savings, achieved by reducing current consumption to ensure sufficient funds for second-period consumption. The HFL agent invests in risky assets, as their expected return is greater than the deposit return, while the LFL agent can only save in deposits. After the CBDC introduction, the LFL agent gains access to an additional savings device but continues to allocate mainly to deposits due to their higher return relative to CBDC.

For the HFL agent, the higher return on risky assets result in higher wealth in the second period, allowing them to meet both consumption and liquidity needs. After the CBDC introduction, the HFL agent allocates around 45% of liquid assets in CBDC. This value is relatively stable across all income levels and close to the optimum from a pure liquidity perspective, equation (34). In contrast, the LFL agent, who cannot invest in risky assets,

Figure 9: Portfolio allocation with deterministic income



Note: This figure shows the portfolio allocation for high- and low-financially literate agents when the maximum and minimum second-period incomes are identical. Dashed lines represent pre-CBDC allocations, while solid lines show allocations after CBDC introduction. Values are relative to the first-period endowment $y = 1$.

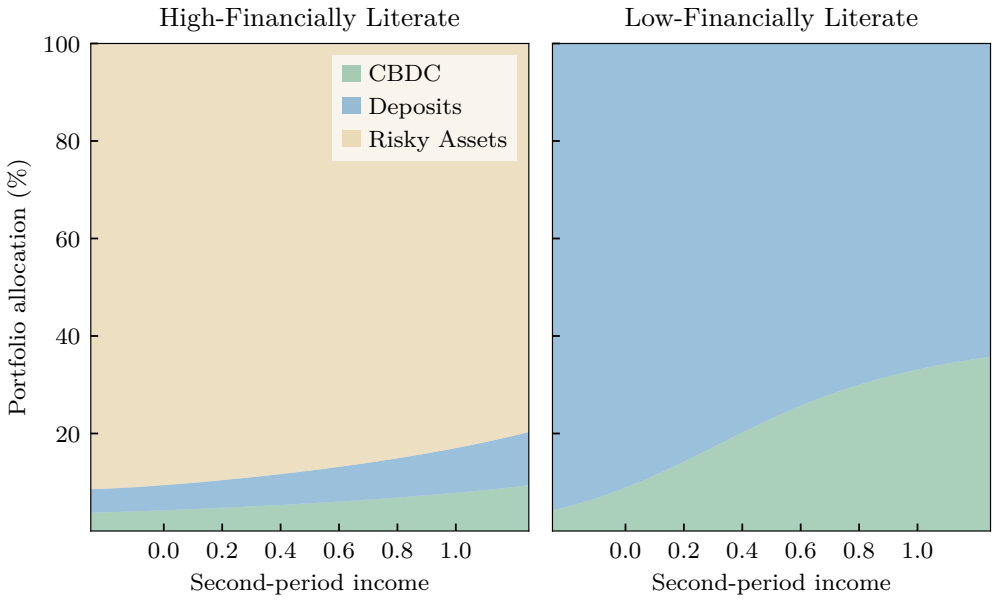
must rely on the higher-return saving option (i.e., deposits) to sustain their second-period consumption. Consequently, the LFL agent prioritizes deposits over CBDC, resulting in a portfolio with a CBDC allocation that does not exceed 36% across income levels, further diverging from the optimal liquidity allocation compared to the HFL agent. Note that for most income values the LFL agent's reduction in deposits is greater than the shift to CBDC, so they substitute from deposits to CBDC less than one-for-one. This is because holding CBDC is costly due to its lower return.

Despite the LFL agent's preference for deposits across different second-period income values, they allocate more wealth to CBDC than the HFL agent both in absolute terms, as shown in Figure 9, and in relative terms within their total portfolio value, with the HFL agent allocating from 4% to 9% to CBDC and the LFL agent ranging CBDC allocation from 4% to 36% depending on second-period income values, as illustrated in Figure 10.

This pattern qualitatively aligns with the empirical findings in Section 4.3, where low-financially literate households show a greater probability of participating following the introduction of a new financial instrument than high-financially literate households.[16] In the model, this difference arises because the HFL agent uses risky assets to safeguard against

[16]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.

Figure 10: Portfolio composition with deterministic income after CBDC introduction



Note: This figure shows the portfolio composition for high- and low-financially literate agents with deterministic income after CBDC introduction.

income risk. Consequently, this distinct portfolio behavior illustrates how financial literacy shapes not only access to assets but also the extent of participation in CBDC.

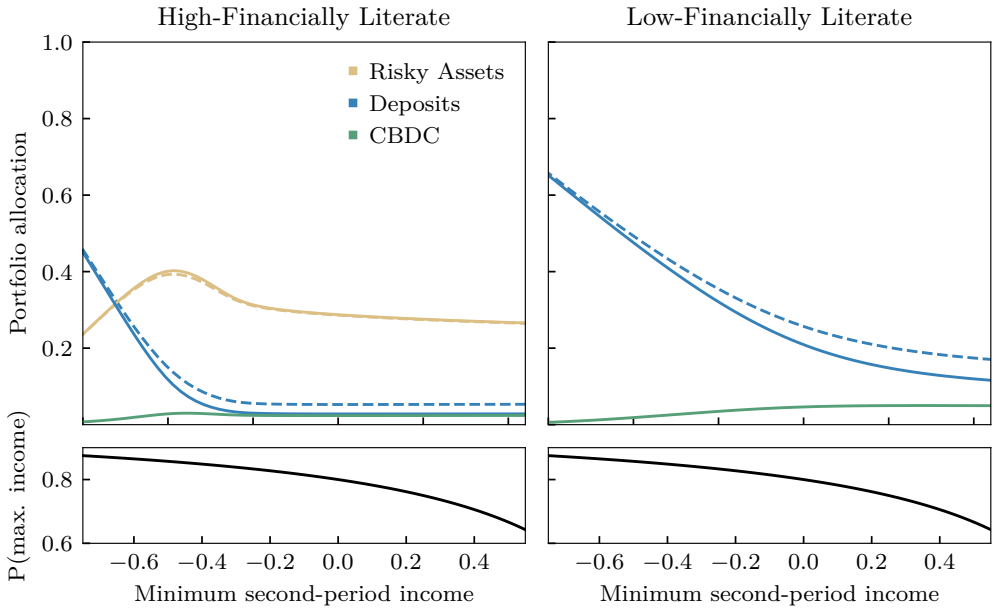
5.4.2 Stochastic second-period income

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 SHIW earnings data.[17]

Figure 11 illustrates how agents allocate their initial endowment, $y = 1$, in their portfolios as a function of minimum second-period income values. Dashed lines represent the pre-CBDC allocations, while solid lines show allocations following the CBDC introduction.

[17]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



Note: This figure shows the portfolio allocation for high- and low-financially literate 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 the expected income constant by adjusting the probability of positive income, as shown in the lower panel. Values are relative to the first-period endowment $y = 1$.

To explore the 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:

$$p^{\epsilon}(s_{\min}) = \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}}. \tag{35}$$

This approach allows me to analyze the effect of uncertainty alone, as the expected income remains fixed and equal to 1. This is in contrast with the deterministic scenario in Figure 9, where I vary the expected income (i.e., $\mathbb{E}[\epsilon] = s$). As the minimum income becomes more negative (i.e., moving left in Figure 11), income variance increases, where the variance is

$$\text{Var}(\epsilon) = p^{\epsilon} s_{\max}^2 + (1 - p^{\epsilon}) s_{\min}^2 - \mathbb{E}^2[\epsilon]. \tag{36}$$

Substituting equation (35), income variance as a function of the minimum income becomes

$$\text{Var}(\epsilon) = (s_{\max} - \mathbb{E}[\epsilon])^2 \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}} + (s_{\min} - \mathbb{E}[\epsilon])^2 \frac{\mathbb{E}[\epsilon] - s_{\min}}{s_{\max} - s_{\min}}. \tag{37}$$

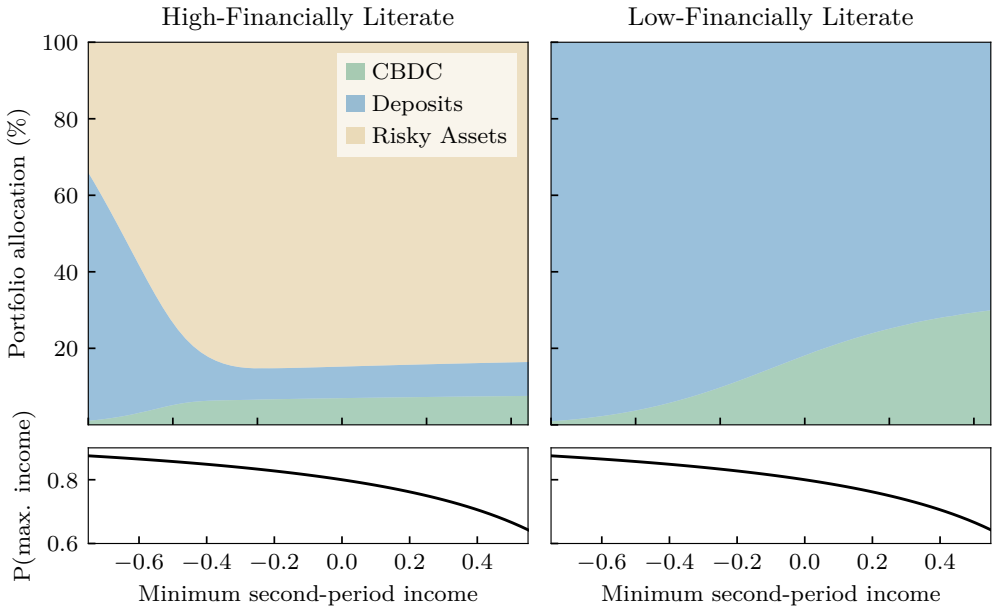
Thus, the variance increases with more negative values of the minimum income.

This income uncertainty leads to deviations from the optimal allocation considered purely from a liquidity perspective, as in the deterministic scenario. 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 because agents must uphold a positive level of consumption in the second period, as captured in the constraints shown in equations (15), (19), (25), and (29). Agents ultimately reach a stable configuration for liquid asset allocation beyond a particular threshold for the minimum income, with the HFL agent achieving stability at a less negative income level.

For the HFL agent, the risky asset allocation is a hump-shaped function of the minimum income. For moderate values of $s_{\min}$, risky assets provide a hedge against low-income scenarios, but as the minimum income becomes more negative, a tipping point occurs where risk becomes too high, causing the HFL agent to shift toward safer assets.

In summary, as income uncertainty increases, the financial behavior of the agents converges: the HFL agent reallocates away from risky assets toward safer, liquid instruments. Nevertheless, even with stochastic income, the LFL agent holds more CBDC than the HFL agent in absolute and relative terms, as illustrated in Figure 12.

Figure 12: Portfolio composition with stochastic income after CBDC introduction



Note: This figure shows the portfolio composition for high- and low-financially literate agents with stochastic income after CBDC introduction.

5.5 Sensitivity analysis of CBDC parameters

Lastly, I explore the sensitivity of the model results to changes in key parameters related to CBDC.

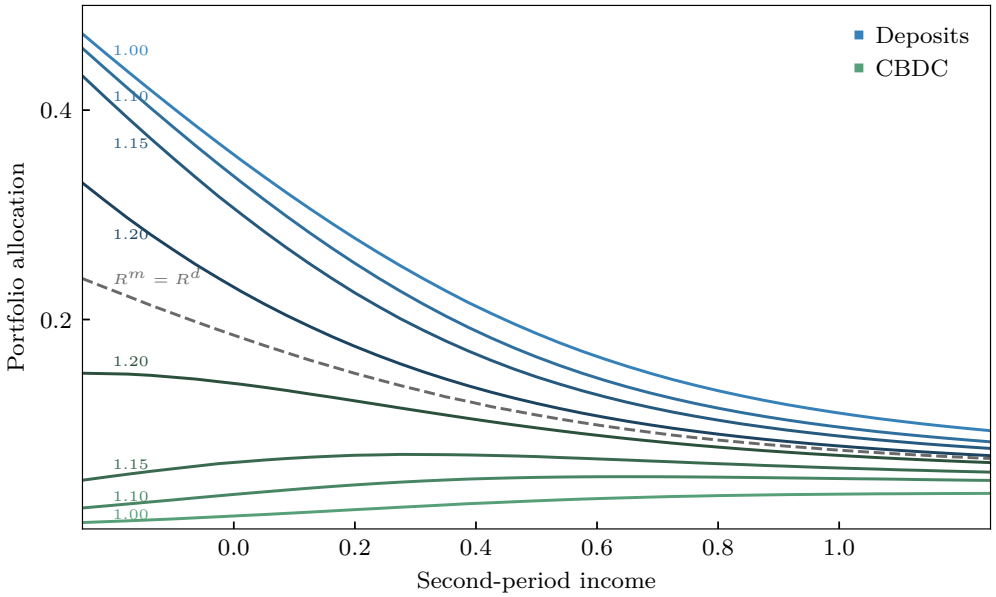
Starting with the inverse elasticity of substitution between CBDC and deposits, σ, changes in this parameter are straightforward to interpret. In the baseline case with a high value of σ (i.e., $\sigma = 1/3$), CBDC and deposits are less substitutable, and are considered complements in the household's portfolio. Consequently, the household prefers to hold both assets to benefit from their combined utility rather than relying on just one. In contrast, for low values of σ [e.g., $\sigma = 1/20$ as considered by Bacchetta and Perazzi (2022)], CBDC and deposits are highly substitutable, and the household holds more of the asset with the higher return.

The baseline model assumes a positive yet return-dominated CBDC rate of $R^m = 1.10$. I vary the CBDC return and show how agents' optimal liquidity allocations shift as a result. Figure 13 shows the changes in the LFL agent's portfolio allocations after CBDC introduction as a function of different CBDC return values. The figure presents model solutions for CBDC returns ranging from the limit case of non-interest-bearing CBDC (i.e., $R^m = 1.00$), represented by the lightest color, to the case where the CBDC return approaches the deposit return (i.e., $R^m = 1.20$), shown with the darkest color. Even with a non-interest-bearing CBDC, the LFL agent allocates a positive share of wealth to CBDC, reflecting its value as a

liquid asset, and the qualitative results hold. As the CBDC rate gets closer to the deposit rate, the optimal allocation for CBDC and deposits converge, and in the limit where the rates are equal (i.e., $R^m = R^d \simeq 1.22$), the allocations coincide, as indicated by the dashed line.

For low values of second-period income (e.g., $s = 0$), the elasticities of CBDC and deposit shares to changes in CBDC return are approximately 0.63 and -0.63, respectively, within the range of CBDC returns considered. The fact that the two elasticities nearly sum to zero indicates that there are no significant changes in first-period consumption. However, as second-period income increases to unity, this is no longer the case, with the elasticities of CBDC and deposit shares becoming 0.18 and -0.16, respectively, and first-period consumption decreases as the CBDC return increases. The portfolio behavior of the HFL agent, not shown, follows a similar pattern to that of the LFL agent, with their allocation to risky assets remaining invariant to changes in the CBDC return.[18]

Figure 13: Portfolio allocation for the low-financially literate agent with deterministic income as a function of CBDC return



Note: This figure shows the portfolio allocation in the CBDC economy for the low-financially literate agent when the maximum and minimum second-period incomes are identical. Model solutions are presented for different values of CBDC return, R^m, equal to $1.00, 1.10, 1.15$, and 1.20, with light color lines corresponding to lower returns. The dashed line indicates the case for $R^m = R^d \simeq 1.22$, where the allocations for CBDC and deposits coincide. Values are relative to the first-period endowment $y = 1$.

[18] In the case of stochastic second-period income, agents' optimal liquidity allocations shift in a qualitatively similar way as the CBDC return changes, as illustrated in Figure D.1 in Appendix D.

6 Conclusion

Government policies have the potential to increase participation in financial markets, which is judged to be inefficiently low. This paper evaluates 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 a 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 reveal that financial literacy positively impacts household likelihood to participate after the introduction of the new policy. Interestingly, the effect is non-monotonic, with households exhibiting some but low financial literacy being more likely to participate compared to the financially illiterate and highly literate groups. The results also suggest that households reallocate their portfolios differently depending on their financial literacy following the new policy, shifting from other securities and stocks to Treasury bonds, highlighting the key role of financial literacy in reshaping household financial behavior.

Building on these empirical insights, I construct a theoretical model to explore how financial literacy impacts CBDC demand through portfolio allocation decisions. The model captures two main economic motives behind CBDC adoption: a liquidity motive, whereby agents derive utility from holding liquid assets (deposits and CBDC), and a risk-sharing motive, whereby the high-financially literate agent can use risky assets to safeguard against income risk. These channels interact with households' financial literacy, which determines access to risky investments. The low-literacy agent, limited in their access to risky investment options, relies more on liquid safe assets, while the high-literacy agent adjusts their portfolio by balancing risk and liquidity needs. This allocation pattern, similar to the empirical finding, underscores how households with some but low financial literacy may be more likely to participate in the CBDC market.

While not a perfect substitute, retail Treasury bonds offer a suitable comparative proxy for studying CBDC adoption. As mentioned previously, both instruments are claims on the government and are household-oriented. While retail Treasury bonds are investments and many central banks envision CBDC primarily as a means of payment, I consider a CBDC useful for both transactional and store-of-value purposes, similar to Li (2023). In the theoretical model, CBDC is interest-bearing but return-dominated by deposits. Although central banks are currently considering non-interest-bearing CBDC designs, the sensitivity analysis shows that as long as CBDC remains return-dominated, the core results are robust, including in the case of a non-interest-bearing CBDC.

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 A.1: 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		

Note: 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 and are subject to a 12.5% tax rate.
Source: Italian Ministry of Economy and Finance.

Table A.2: 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
Interest	-	-	50.12	49.59
Mortgages	65.97	58.38	-	-
Average	55.09	49.57	54.39	54.47

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

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?[19]

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?[20]

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

[19] 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.

[20] 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 Mortgages

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?[21]

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

A.2 Descriptive statistics

Table A.3 shows the statistics for the financial literacy score across various demographic groups, highlighting disparities based on factors such as education, age, gender, marital status, employment, and risk aversion. The mean score increases significantly with higher educational qualifications, while the increase in the population of the municipality of residence is relatively modest. Financial literacy scores tend to rise with age but decrease for individuals over 65, consistent with existing literature [e.g., Lusardi and Mitchell (2022)]. Males, on average, have higher scores than females, and married individuals score higher than single individuals. Employment status also appears to matter, with employed individuals showing higher scores on average than those not employed. Additionally, the mean score is decreasing in risk aversion. These statistics highlight the disparities in financial literacy across different demographic groups. Figure A.1 further illustrates these disparities by showing the regional distribution of financial literacy scores in Italy. Regions in the North generally exhibit higher scores than those in the South, with overall variation in scores ranging from 1.3 to 1.9.

In addition to demographic and regional differences, another important dimension of financial literacy is its relationship with financial wealth. Figure A.2 shows the wealth distribution across financial literacy scores. Households in the upper wealth brackets present higher financial literacy scores (2 and 3), while households in the lower wealth groups, particularly in the 0–20 k€ range illustrated in the left panel, show lower financial literacy scores (0 and 1). This suggests a positive correlation between financial literacy and wealth accumulation.

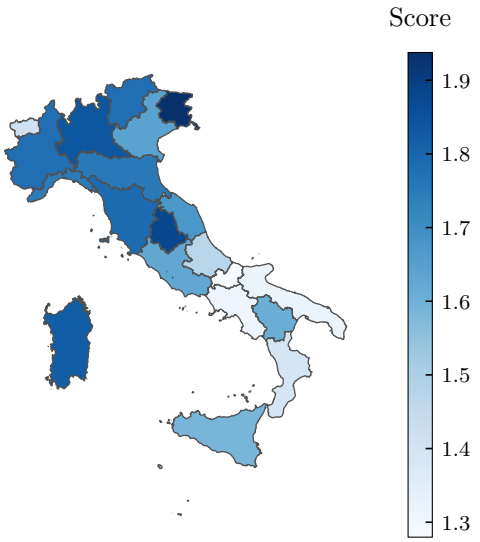
[21] In the 2006 and 2008 waves, the answer "No answer" is not available.

Table A.3: Financial literacy score by demographics

Variable	Mean	Std	N
Educational qualification			
None	0.74	0.92	1,115
Elementary school	1.21	1.02	6,469
Middle school	1.65	0.97	10,025
High school	1.93	0.88	7,695
Bachelor's degree	2.09	0.88	3,865
Post-graduate qualification	2.17	0.88	418
Age			
Up to 30	1.65	0.96	828
31 - 40	1.75	0.92	2,683
41 - 50	1.79	0.92	5,180
51 - 65	1.82	0.95	9,262
More than 65	1.44	1.07	11,634
Gender			
Male	1.79	0.96	17,173
Female	1.47	1.04	12,414
Marital status			
Married	1.77	0.96	17,883
Single	1.49	1.05	11,704
Work status			
Employed	1.88	0.91	12,636
Not employed	1.49	1.04	16.951
Municipality Population			
Up to 5,000	1.59	1.00	3,317
5,000 - 20,000	1.60	0.97	3,962
20,000 - 50,000	1.66	1.00	8,584
50,000 - 200,000	1.68	1.02	9,222
More than 200,000	1.70	1.00	4,502
Risk aversion			
Low	1.83	0.98	311
Medium	1.78	0.96	13,601
High	1.55	1.03	15,675

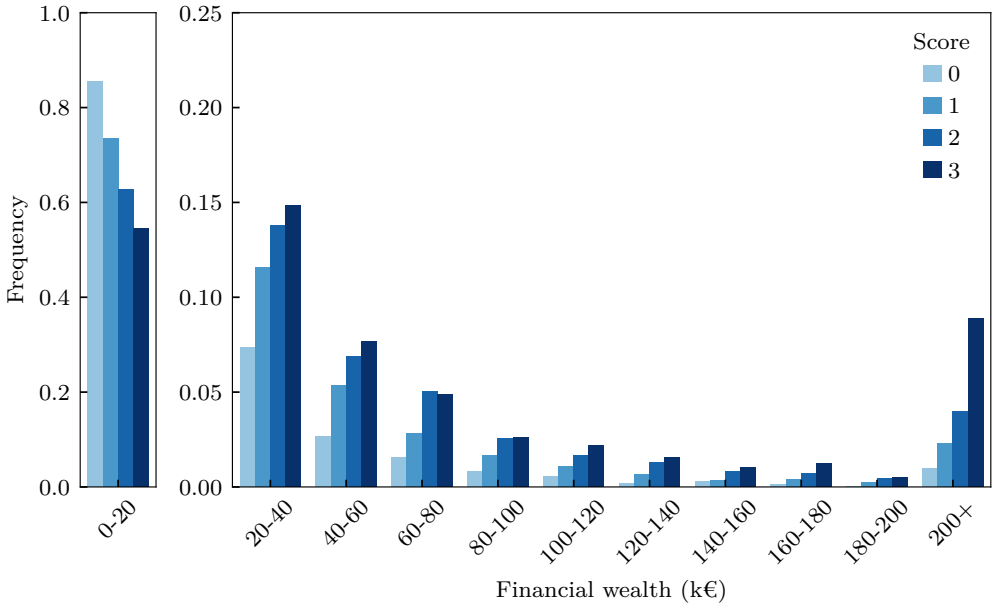
Note: This table reports the mean and standard deviation of the financial literacy score by demographic variables, where the range of possible scores goes from 0 to 3. Single includes singles, divorced, and widowed individuals. Employed respondents include employees and self-employed individuals.
Source: SHIW and author calculations.

Figure A.1: Financial literacy score across Italian regions



Note: This map shows the average financial literacy score across Italian regions. The full range of possible scores goes from 0 to 3.
Source: SHIW and author calculations.

Figure A.2: Wealth distribution across financial literacy scores



Note: This figure shows the wealth distribution for each financial literacy score level. Wealth is measured as total financial wealth, categorized into intervals of €20,000. The distribution reflects the average over the sample.
Source: SHIW and author calculations.

B Empirical results

B.1 Logit odds ratios

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

$$z = \hat{\beta}(D^{12} \times LS^{10}) + \mathscr{A}, \quad \mathscr{A} = \hat{\alpha} + \sum_{\ell=1}^{3} \hat{\gamma}_\ell LS_\ell^{10} + \hat{\boldsymbol{\eta}}^\intercal \boldsymbol{X}, \tag{B1}$$

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

Recalling that the propensity to participate is estimated with a logistic function, as in equation (1), the differential policy-financial literacy effects when the interaction term $D^{12} \times LS^{10}$ is equal to 1 and 0 are, respectively:

$$\ln\left(\frac{P_1}{1-P_1}\right) = \hat{\beta} + \mathscr{A}, \qquad \ln\left(\frac{P_0}{1-P_0}\right) = \mathscr{A}. \tag{B2}$$

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 $\mathscr{A}$:

$$\ln\left(\frac{P_1}{1-P_1}\right) - \ln\left(\frac{P_0}{1-P_0}\right) = \hat{\beta}. \tag{B3}$$

Taking exponents on both sides gives the odds ratio:

$$\frac{P_1}{1-P_1} = \frac{P_0}{1-P_0} \times \exp(\hat{\beta}). \tag{B4}$$

Table B.1: Logit estimation results

Dep. Var.:	Treasury bond		Other Govt. Bond		Stocks	
Market Participation	(1)	(2)	(3)	(4)	(5)	(6)
$D^{12} \times LS^{10}$	$0.14^{***}(0.05)$		$-0.21^{***}(0.03)$		$-0.05^{**}(0.03)$	
$D^{12} \times LS_1^{10}$		$0.59^{**}(0.26)$		$-0.28^{**}(0.13)$		$-0.24^{***}(0.09)$
$D^{12} \times LS_2^{10}$		$0.22^{*}(0.13)$		$-0.42^{***}(0.09)$		$-0.13^{**}(0.06)$
$D^{12} \times LS_3^{10}$		$0.45^{*}(0.26)$		$-0.63^{***}(0.18)$		0.05 (0.17)
LS_1^{10}	$1.27^{***}(0.48)$	$1.00^{*}(0.51)$	$0.91^{***}(0.20)$	$0.94^{***}(0.21)$	$1.35^{***}(0.23)$	$1.44^{***}(0.23)$
LS_2^{10}	$1.84^{***}(0.46)$	$1.88^{***}(0.46)$	$1.22^{***}(0.20)$	$1.22^{***}(0.20)$	$1.72^{***}(0.22)$	$1.73^{***}(0.22)$
LS_3^{10}	$1.31^{**}(0.51)$	$1.29^{**}(0.53)$	$1.32^{***}(0.22)$	$1.31^{***}(0.23)$	$0.95^{***}(0.25)$	$0.85^{***}(0.26)$
Age	$0.10^{**}(0.04)$	$0.10^{**}(0.04)$	$0.08^{***}(0.03)$	$0.08^{**}(0.03)$	$0.12^{***}(0.02)$	$0.12^{***}(0.02)$
Age^2	$0.00^{*}(0.00)$	$0.00^{*}(0.00)$	$0.00^{**}(0.00)$	$0.00^{**}(0.00)$	$0.00^{***}(0.00)$	$0.00^{***}(0.00)$
Married	0.29 (0.19)	0.29 (0.19)	0.08 (0.11)	0.09 (0.11)	0.14 (0.09)	0.14 (0.09)
Female	$-0.29^{*}(0.18)$	-0.29 (0.18)	-0.02 (0.10)	-0.02 (0.10)	$-0.51^{***}(0.09)$	$-0.50^{***}(0.09)$
High-Risk Aversion	$-1.13^{***}(0.18)$	$-1.14^{***}(0.18)$	$-0.19^{**}(0.09)$	$-0.19^{**}(0.09)$	$-1.08^{***}(0.09)$	$-1.08^{***}(0.09)$
Constant	$-8.10^{***}(1.47)$	$-8.05^{***}(1.47)$	$-6.45^{***}(0.84)$	$-6.44^{***}(0.84)$	$-5.79^{***}(0.67)$	$-5.81^{***}(0.67)$
Pseudo R^2	0.017	0.017	0.016	0.016	0.065	0.065

Note: This 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.
Columns (1), (3), and (5) refer to specification (2), while columns (2), (4), and (6) refer to specification (5).
In specification (5), the baseline financial literacy level is 0. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

C Theoretical model

C.1 Optimal conditions

In the pre-CBDC economy, the HFL agent's first-order condition for risky assets, $\partial \mathbb{E}[\mathscr{U}^h]/\partial a = 0$, is:

$$\frac{1}{y-a-d^h} = \beta\Bigg\{\bar{R}^a p^a\left[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\min}}\right] + \underline{R}^a(1-p^a)\left[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\min}}\right]\Bigg\}. \tag{C1}$$

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

$$\frac{1}{y-a-d^h} = \beta R^d\Bigg\{p^a\left[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + s_{\min}}\right] + (1-p^a)\left[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\min}}\right]\Bigg\} + \frac{\gamma}{d^h}. \tag{C2}$$

While the LFL agent's first-order condition, $\partial \mathbb{E}[\mathscr{U}^l]/\partial d^l = 0$, is:

$$\frac{1}{y-d^l} = \beta R^d\left[\frac{p^\epsilon}{R^d d^l + s_{\max}} + \frac{1-p^\epsilon}{R^d d^l + s_{\min}}\right] + \frac{\gamma}{d^l}. \tag{C3}$$

After the CBDC introduction, the HFL agent's first-order conditions for risky assets, deposits, and CBDC are, respectively:

$$
\begin{aligned}
a: \quad \frac{1}{y-a-d^h-m^h} = \beta\Bigg\{ & \bar{R}^a p^a \Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \\
& + \underline{R}^a (1-p^a) \Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \Bigg\}, \qquad \text{(C4)} \\
d^h: \quad \frac{1}{y-a-d^h-m^h} = \beta R^d \Bigg\{ & p^a \Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \\
& + (1-p^a) \Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \Bigg\} \\
& + \gamma \Bigg[\frac{(d^h)^{-\sigma}}{(d^h)^{1-\sigma} + \lambda (m^h)^{1-\sigma}} \Bigg], \qquad \text{(C5)} \\
m^h: \quad \frac{1}{y-a-d^h-m^h} = \beta R^m \Bigg\{ & p^a \Bigg[\frac{p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\bar{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \\
& + (1-p^a) \Bigg[\frac{p^\epsilon}{\underline{R}^a a + R^d d^h + s_{\max}} \\
& \qquad + \frac{1-p^\epsilon}{\underline{R}^a a + R^d d^h + R^m m^h + s_{\min}} \Bigg] \Bigg\} \\
& + \gamma\lambda \Bigg[\frac{(m^h)^{-\sigma}}{(d^h)^{1-\sigma} + \lambda (m^h)^{1-\sigma}} \Bigg], \qquad \text{(C6)}
\end{aligned}
$$

and the LFL agent's first-order conditions for deposits and CBDC are, respectively:

$$d^l: \quad \frac{1}{y-d^l-m^l} = \beta R^d \left[\frac{p^\epsilon}{R^d d^l + R^m m^l + s_{\max}} + \frac{1-p^\epsilon}{R^d d^l + s_{\min}} \right] + \gamma \left[\frac{(d^l)^{-\sigma}}{(d^l)^{1-\sigma} + \lambda (m^l)^{1-\sigma}} \right], \tag{C7}$$

$$m^l: \quad \frac{1}{y-d^l-m^l} = \beta R^m \left[\frac{p^\epsilon}{R^d d^l + R^m m^l + s_{\max}} + \frac{1-p^\epsilon}{R^d d^l + s_{\min}} \right] + \gamma \lambda \left[\frac{(m^l)^{-\sigma}}{(d^l)^{1-\sigma} + \lambda (m^l)^{1-\sigma}} \right]. \tag{C8}$$

C.2 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 a representative mix of 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 years in recent periods [Board of Governors of the Federal Reserve System (2021)]. The low return reflects the worst-case scenario if 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:

$$\text{Equity premium} = \mathbb{E}[r^a] - r^d, \tag{C9}$$

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

$$r^a = \begin{cases} \bar{r}^a = 1.09 & \text{with probability } f^a = 0.95, \\ \underline{r}^a = 0.6 & \text{with probability } 1 - f^a = 0.05. \end{cases} \tag{C10}$$

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

$$R^a = \left\{ (\bar{r}^a)^{(T-n)} (\underline{r}^a)^n \quad \text{with probability } P = \binom{T}{n} (f^a)^{(T-n)} (1-f^a)^n, \right. \tag{C11}$$

where n represents the number of crisis years. For example, assuming a period duration of

20 years and considering probabilities as in equation (C10), the case of one crisis year has a return on the risky assets equal to

$$R_1^a = (1.09)^{19}(0.6)^1 = 3.08, \tag{C12}$$

and happens with probability

$$P_1 = \binom{20}{1}(0.95)^{19}(0.05)^1 = 0.38. \tag{C13}$$

The possible outcomes over the period are reported in Table C.1.

Table C.1: Stochastic risky asset return over the period

n	P_n	R_n^a
0	0.358	5.60
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 bin the outcomes into two events: a high-return event and a low-return event. The high return occurs with the probability

$$p^a = P_0 + P_1 + P_2 = 0.92, \tag{C14}$$

and gives a weighted average return of

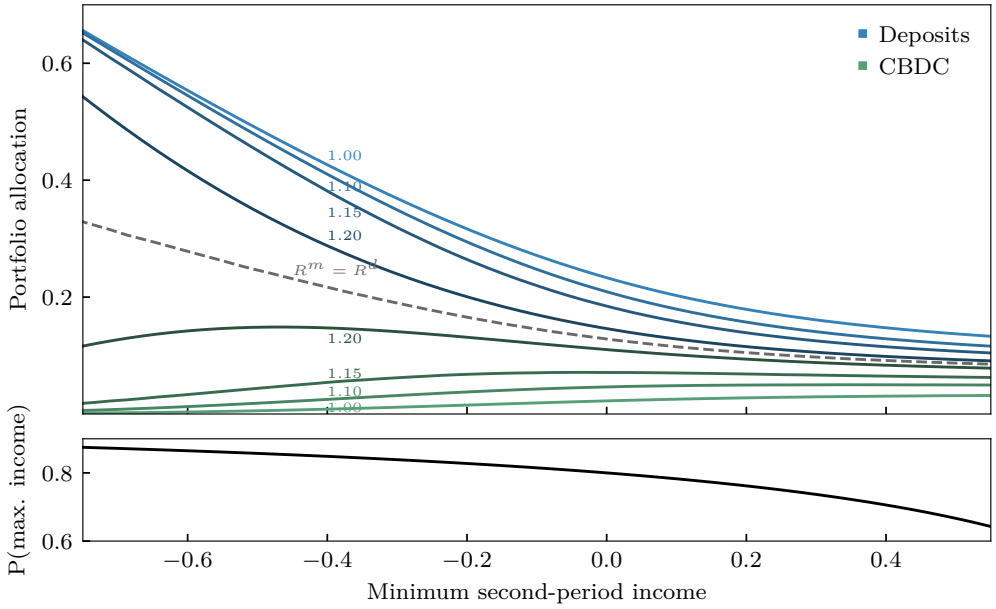
$$\bar{R}^a = \frac{P_0 R_0^a + P_1 R_1^a + P_2 R_2^a}{P_0 + P_1 + P_2} = 3.77. \tag{C15}$$

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

$$\underline{R}^a = \frac{P_3 R_3^a + P_4 R_4^a + P_5 R_5^a}{P_3 + P_4 + P_5} = 0.83. \tag{C16}$$

D Additional figures

Figure D.1: Portfolio allocation for the low-financially literate agent with stochastic income as a function of CBDC return



Note: This figure shows the portfolio allocation in the CBDC economy for the low-financially literate agent with stochastic income. Model solutions are presented for different values of CBDC return, R^m, equal to $1, 1.10, 1.15$, and 1.20, with light color lines corresponding to lower returns. The dashed line indicates the case for $R^m = R^d \simeq 1.22$, where the allocations for CBDC and deposits coincide. Values are relative to the first-period endowment $y = 1$.