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THE MATTHEW EFFECT AND MODERN FINANCE: ON THE NEXUS BETWEEN WEALTH INEQUALITY, FINANCIAL DEVELOPMENT AND FINANCIAL TECHNOLOGY

by Jon Frost[*], Leonardo Gambacorta[§] and Romina Gambacorta[♣]

Abstract

This paper analyses the role of financial development and financial technology in driving inequality in (returns to) wealth. Using micro data from the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy for the period 1991–2016, we find evidence of the "Matthew effect" – a capacity of wealthy households to achieve higher returns than other households. With an instrumental variable approach, we find that financial development (number of bank branches) and financial technology (use of remote banking) both have a positive association with households' financial wealth and financial returns. While households of all wealth deciles benefit from the effects of financial development and financial technology, these benefits are larger when moving toward the top of the wealth distribution. Still, the economic significance of this gap fell in the last part of the sample period, as remote banking became more widespread.

JEL Classification: G10, G21, O15, D63.
Keywords: inequality, financial development, banks, financial technology, fintech.

Contents

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* Bank for International Settlements and Cambridge Centre for Alternative Finance.

§ Bank for International Settlements and CEPR.

♣ Bank of Italy, Directorate General for Economics, Statistics and Research, Statistical Analysis Directorate.

1. Introduction[1]

In the social sciences, the idea of the well-endowed receiving further privilege, e.g. the rich getting richer, is often called the "Matthew effect" (Merton, 1968). This comes from the New Testament Book of Matthew (25:29), in which it is written: "*For unto every one that hath shall be given, and he shall have abundance: but from him that hath not shall be taken away even that which he hath*".

In economics, this is relevant particularly with regard to wealth and income inequality. By various mechanisms, accumulated differences could lead to a more skewed wealth or income distribution over time. For instance, a key idea of Piketty (2014) is that if real interest rates are persistently higher than real output growth, this will lead to rising wealth inequality – particularly if wealthier households achieve higher-than-average returns. Piketty tests this by comparing the returns on large university endowments in the United States. By this mechanism, and through compounding, the wealthy may accumulate an even larger scale of private capital over time. A similar concern was raised by Keynes (1923), who warned that this accumulation could lead to growing inequality.[2]

To date, the economics literature has often explained the accumulation effect and the rise in inequality based on personal abilities such as entrepreneurial talent, risk appetite, and financial skills (e.g. Galor and Moav, 2004; Guiso et al., 2018).[3] The effects of financial development and advances in financial technology have received less attention. However, a higher level of financial development could give wealthier families privileged access to better financial services or to assets with higher returns. *A priori*, it could be expected that for low levels of financial development, greater access to financial services could help the poor to borrow, invest and smooth shocks over time (relative to more traditional, e.g. informal forms of finance), thus reducing wealth inequality. At very high levels of financial development, as in many advanced economies today, a larger financial sector may mean more opportunities for the wealthy to save and invest, and perhaps to achieve higher returns than other savers. The proliferation of hedge funds, family offices and other alternative investment vehicles that are the domain of only the wealthy would hint that such effects might be visible (Kay, 2015; Rajan, 2010).

Technological advances could play a role, as well. While there is a large literature on the link between technological changes, such as automation, and income inequality (see e.g. Acemoğlu, 2002; Jaumotte et al., 2013), there has been less research on how technology-enabled innovation in financial services (fintech) may influence investment returns. This is becoming ever more important as fintech innovations become more widely adopted around the world.[4] Banking services can now be delivered digitally, for instance through

[1] We would like to thank Stijn Claessens, Giovanni D'Alessio, Marco Bottone, Nicola Branzoli, Sebastian Doerr, Giuseppe Ilardi, Enisse Kharroubi, Luiz Pereira da Silva, Goetz von Peter, Alfonso Rosolia, Hyun Song Shin, Egon Zakrajsek and seminar participants at the Bank of Italy and Bank for International Settlements for comments and suggestions. We thank Giulio Cornelli and Haiwei Cao for excellent research assistance. The views expressed are those of the authors and not necessarily of the Bank of Italy or the Bank for International Settlements.

[2] To some extent, such accumulation is the converse of the process that Keynes (1936) would later call "the euthanasia of the rentier", or a decline in the scarcity-value of capital and hence the returns of the wealthy.

[3] A further driver of changes in wealth distribution is changes in asset prices. In Italy, capital gains have contributed substantially to the accumulation of overall net wealth (i.e. both real and financial assets) in the last decades. This contribution is lower than that of savings, but higher than that of inheritances and gifts, and has had a substantial distributional impact (see Cannari et al., 2007; D'Alessio, 2012).

[4] For an overview of fintech innovations and the scale of their adoption, see FSB (2017) and Frost (2020).

online banking, chatbots and robo-advice, and many banks are downsizing their physical operations. As bank customers are relying less on branches because of digital banking, it is also important to investigate how the effects such technological advances interact with the effects of physical branches.

In this paper we consider access to retail banking through bank branches (an indicator of financial development) and remote banking (a form of financial technology advances). Greater access to banking services should give consumers greater opportunities to borrow and save. More competition (due to more bank branches or access to remote banking) should allow for more attractive products with lower mark-ups. Italy is a particularly relevant country in which to study these effects, given the wealth of household survey data, the large diversity across households and regions, and the relevant changes in the variables of interest over time. Bank branches are widespread across Italy, but with large differences by province. The number of branches has initially risen and then fallen in our sample period. The use of remote connections also shows substantial variation by region and time. Remote banking has allowed financial services to be supplied (at a non-negligible scale) since 1995, with the bank Cassa di Risparmio delle Provincie Lombarde (Cariplo). At that time, the use of home banking required the application of a personal computer (PC) client and had a fixed cost per client. However, a substantial rise in remote banking in Italy started in 1999 when other financial intermediaries began to offer home banking services for free by means of an internet browser. In 2016, 25% of Italian households actively used remote banking, including through smartphone applications.

The main research questions of this paper are:

1. Do financial sector development and financial technology advances contribute to higher financial returns?
2. Are these effects different for the wealthy than others? Do they lead to greater wealth inequality?
3. Do the above effects change over time, in particular as technology becomes more diffused?

The empirical analysis uses micro data gathered from the Italian Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy (Bank of Italy, 2018; Baffigi et al., 2016) over the period 1991–2016. Information on households' wealth and financial returns has been merged with indicators of financial development of the territory in which the family resides (including the number of bank branches) to assess whether financial development increase financial returns for wealthier families. The database also includes a measure for households' use of remote banking as one form of fintech adoption. Fintech may have reduced the importance of the territory of residence. At the same time, especially online fund products with minimum investment thresholds may have created new opportunities for higher-wealth households. Because both financial development and financial technology may be correlated with other factors leading to higher wealth and returns, we use instrumental variables – namely financial development in 1989, and access to the internet – in a two-stage estimation approach.

Based on quantile regressions, and controlling for different household characteristics and endogeneity in financial development and financial technology, we find three key results.

1. Financial development and fintech both have a positive impact on financial wealth and the rate of returns on financial wealth when controlling for a range of other

factors. The effect is statistically and economically significant for all quantiles of households by level of financial wealth.

2. While households of all wealth deciles benefit, the above effects increase starkly moving toward the top of the distribution and are particularly strong for the top decile. For the wealthiest decile, a one-standard deviation change in bank branches is associated with financial wealth (a rate of return) that is €33,000 (2.7 percentage points) higher, and access to remote banking is associated with an increase in wealth (returns) of €4,000 (0.28 percentage points).
3. The positive effects of both financial development (bank branches) and fintech (remote connection to banks) on financial wealth and the rate of return on financial wealth are present in both the first period (1991–2002) and second period (2004–2016) of the sample. Yet their economic magnitude, and that of the gap between the wealth and others, is lower in the second period, as the number of bank branches fell and remote connection to banks become more widespread. In both periods, financial development and fintech are largely substitutes.

Our contribution to the literature is thus threefold. First, we document for Italy a higher rate of return for higher-wealth households – a result that is comparable with studies for Norway, Sweden, the Netherlands and India (Fagereng et al., 2020; Calvet et al., 2007; Deuflhard et al., 2019; Campbell et al., 2019). Second, we find for Italy a positive effect of both financial development and technological advances on financial returns and overall financial wealth. However, we find that, when controlling for endogeneity with an instrumental variable set-up, the two effects tend to be substitutes. (With ordinary least squares, their interaction would be positive). Moreover, in more recent years, the effects appear to moderate in parallel with fewer branches and a more widespread use of remote banking services. Results continue to hold when controlling for a set of additional bank characteristics. Third, we identify a new channel through which technology may contribute to greater wealth inequality, in addition to the well-known channels through automation and labour markets. This contributes to new insights on the impact of fintech, along with evidence from the United States (Mihet, 2019; Reher and Sokolinski, 2020). Our findings indicate that while financial technology may provide key benefits to users, it may be that these (if technology is not sufficiently diffused) accrue more to the wealthy. This and financial development may contribute to the broader Matthew effect.

The rest of the paper is organised as follows. Section 2 gives a brief overview of the relevant literature on unequal returns, wealth inequality and fintech. Section 3 discusses the SHIW data and some secular trends. The empirical framework is discussed in section 4, while some potential endogeneity issues and the approach to address them are covered in Section 5. Section 6 presents our main results, and robustness checks and extensions are presented in Section 7. The last section summarises the main conclusions.

2. Literature review

While the notion of inequality in returns to wealth is not new, there is surprisingly little empirical evidence on this to date. This is only recently starting to change.

In the last few years, a few studies have provided evidence on inequality of returns within specific countries, in some cases related to specific financial factors. For instance, using administrative data from Norway, Fagereng et al. (2020) find higher returns on financial assets and net wealth among wealthier households, which they call "scale dependence".[5] For Sweden, Calvet et al. (2007) find that more sophisticated households are more likely to have financial investments and to invest efficiently. In a similar spirit, using Dutch household survey data, Deuflhard et al. (2019) find that a one-standard deviation increase in financial literacy is associated with a 12% increase in returns on saving accounts. They find that online accounts are one channel through which financial literacy has a positive association with returns. Using data on stock portfolios in India, Campbell et al. (2019) find that larger accounts diversify more effectively than smaller accounts, and thus achieve higher log returns over time. For the United States, Saez and Zucman (2016) show mildly increasing pre-tax returns in wealth over the period 1980–2012 – but flat or mildly decreasing post-tax returns in wealth. Benhabib and Bisin (2018) put these studies into the broader context of theoretical and empirical literature on wealth distribution.

Meanwhile, a growing literature looks at financial structure and income inequality, e.g. Brei et al. (2018). Using data for a panel of 97 economies over the period 1989–2012, the authors find that the relationship is not monotonic. Up to a point, more finance reduces income inequality. Beyond that point, inequality rises if finance is expanded via market-based financing, while it does not when finance grows via bank lending. Allen et al. (2018) investigate the impact of financial structure on economic growth and find that: (i) this effect depends on the overall economic development and institutions' characteristics and (ii) market-based systems have an advantage for financially dependent industries in good times, but are a disadvantage in bad times. Luintel et al. (2008) point to the importance of information asymmetries (both moral hazard and adverse selection) in determining how financial markets and financial institutions affect economic growth.

Indeed, relationships may depend on the level of economic development. Especially where the financial system is underdeveloped, finance-induced growth could be pro-poor by expanding employment opportunities (see, amongst others, Demirgüç-Kunt and Levine (2009) for an extensive review and Burgess and Pande (2005) for the Indian case). Yet such growth may also favour entrepreneurs and their profit margins. Cournède et al. (2015) find that for advanced economies, financial expansion can fuel income inequality as higher-income people can benefit more from the greater availability of credit and since the financial sector pays higher wages. The relationship between inequality and economic development was pioneered by Kuznets (1955), who established the inverted U-shaped path of income inequality along economic development (Kuznets curve). At the industrial take-off, Kuznets argued, mean incomes and their dispersion are lower in rural vis-à-vis urban areas. Hence, urbanisation raises inequality. But as new generations of rural people migrate to cities, they can profit from urban opportunities. The wages of lower-income groups rise, narrowing overall inequality. Kuznets' argument of urban opportunities requires financial development, enabling formerly poor migrants to finance an education and build their own businesses – regardless of inherited wealth or lack of it. It is an open whether inequality may increase again after a certain threshold. For instance, Lessmann (2014) finds support for the inverted U-shape path for spatial (interregional) inequality, but finds some evidence that inequality rises again at high levels of development.

Recently, financial technologies (fintech) have started to expand access to financial services. Especially in emerging market and developing economies, mobile money and

[5] For a discussion of scale dependence in the context of income inequality, looking at mechanisms through labour markets and changes in skill prices in the United States, see Gabaix et al. (2016).

other remote services have given borrowers access to new payment and – in many cases – savings products (Demirgüç-Kunt et al., 2018). Philippon (2016) discusses the opportunity of fintech advances to promote competition and bring down the cost of finance. While many fintech providers claim to "democratise" investing, there is limited evidence to critically assess such claims.

Finally, there are a number of studies looking into the impact of technological innovation on inequality. Acemoğlu (2002) discusses how technical change in the latter half of the 20th century has been "skills-biased", leading to greater differentials between skilled and unskilled labour. Jaumotte et al. (2013) discuss the relative contributions of technological progress and globalisation in explaining rising inequality across countries in the period 1981–2003; they find that technological progress has been a more important factor. Recently, Autor et al. (2020) develop a model of "superstar firms" as a driver of the recent fall in the labour share of income.

Two new studies are similar in spirit to our paper, using evidence from the United States. Mihet (2019) assess the impact of technology on participation and price efficiency in the stock market. She shows theoretically and empirically that improvements in financial technology may disproportionately benefit informed, sophisticated (high-wealth) investors. Reher and Sokolinski (2020) find that greater access by to robo-advice has benefitted the middle quintiles of the US wealth distribution relative to wealthier households, but that it has not benefited the bottom quintile of the distribution.

Overall, there is relatively limited evidence on how financial development and fintech may affect returns to wealth of different wealth deciles over time. This paper aims to add evidence to this discussion.

3. Data description

The data source used in our analysis is the Italian Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy since 1962. This survey is particularly useful for our purposes as it collects information on numerous aspects of the socio-economic conditions of the households. This allows us to study the process of wealth accumulation. In particular, the SHIW contains numerous variables on demographic characteristics of members of each household (such as the province of birth and residence, birth year, gender, education, marital status, and work status), detailed information about all income sources and wealth components (real and financial assets, and debts), and the returns on wealth. All the relevant information for our study is available since 1991, allowing us to analyse the evolution of returns to wealth over the last quarter of a century.[6]

Furthermore, the survey collects information about the remote connection to banks, such as online and telephone banking. These technology-enabled innovations aimed at retail bank customers can be seen as an early form of fintech.[7] Finally, as an indicator of the

[6] For more details about the SHIW and the measurement of capital returns see Annex A.

[7] In particular, this variable has been permanently collected since the 2000 wave. To make possible the use of this piece of information for the entire period of analysis, the variable on remote connection with banks has been reconstructed backward using the procedure detailed in Annex B.

degree of financial development of the territory in which the family resides, we use the number of bank branches in the province of residence in the survey year.

Table 1 reports summary statistics for the total sample on the main household-level variables used in the regression analysis over 1991–2016.[8] More than 50% of the households have a head of household who is 50 or older.[9] About 10% of heads of household hold a university degree and just under 60% is employed (including self-employed). Foreign-born households represent 5% of the total sample. Net and financial wealth (mean of €227,000 and €28,000, respectively) show a high level of variability in the sample, as does the rate of financial returns (mean of 2.3%). A remote connection to banks is used by about the 10% of the total sample, with a proportion of users which increases on average over time (from about 1% in 1991 to more than 25% in 2016, Figure B.1 in Annex B). There are persistent differences across Italian geographical areas (Figure 1). The number of bank branches, expressed in terms of resident population, also varies widely across Italy, with lower values in southern Italy and on the islands. The lowest value in 1991, equal to about 1.2 bank branches per 10,000 inhabitants, is in Sardinia. In 2016 the provinces with the lowest values are mostly in Calabria (about 2 bank branches per 10,000 inhabitants). Higher values of the financial development indicator are observed in the northern regions and in particular in the provinces of Vercelli (Piedmont) and Trento (Trentino-South Tyrol). The highest value in the sample is observed in central Italy, in the province of Ascoli Piceno (Marche) with about 13 bank branches per 10,000 inhabitants in 2008. After 1991 the number of bank branches per inhabitants progressively increased in all Italian geographical areas until 2008 and then started to decline. In 2016 the average number of bank branches per inhabitants in Italy was the same as in 2000 (Figure 2).[10] Nonetheless, access to bank accounts has increased over the sample period. Access has risen particularly for traditionally unbanked households, e.g. those whose head of household is female, has no formal educational qualification or was born abroad, and for households in southern Italy and on the islands (Figure 3).

Table 2 presents households' net and financial wealth composition obtained on survey data. Households' net wealth in Italy consists mostly of real assets (and in particular the main residence). According to SHIW, financial assets only represent a share of between 9 and 16% of net assets in the sample period.[11] About half of the financial wealth is in deposits; the share of government securities has diminished over time (from almost 35% in 1991 to less than 9% in 2016).

[8] Figure and tables are reported at the end of the paper. All figures in the paper refer to euro values expressed at constant prices (thousands of 2016 euro) calculated using the deflator of final consumption expenditure of resident households of the national accounts.

[9] Individual characteristics refer to the head of household, defined as the member with the highest level of individual income.

[10] This decline may reflect reduced demand as consumers substitute to remote banking. Indeed, Carmignani et al. (2020) show that over 2012–15, the reduction in the number of bank branches was more intense for those local markets where the diffusion of digital banking services was higher in 2012.

[11] It is worth noting that this share is underestimated due to the fact that, in face to face interviews, conducted at the households' home, the value of the main residence is usually quite accurate while other components of wealth, such as other dwellings and financial assets, are under-reported. As a consequence, the share of wealth in the latter component is usually under-estimated. In particular, the share of financial assets in households wealth derived by the SHIW is much lower from that inferable from the financial accounts. For more details see Bonci et al. (2005).

Portfolio composition is quite different among wealth deciles and has varied over time (see Table 3). The poorest households mainly hold only deposits (and government bonds in the early 1990s). Other assets mostly appear in the portfolio of households starting from the median wealth level. The wealthiest households show a much higher degree of diversification of their portfolio, which has become more evident over time.[12] Holding of more complex assets is mostly concentrated among wealthy families. In 2016, the top decile of the distribution by wealth invested 8% of their financial wealth in equities and 40% in other private securities (such as bonds, mutual funds, foreign securities, loans to cooperatives). These percentages are 0.5% and 10% respectively for the median household and virtually zero for the bottom two deciles of the wealth distribution.

Both the mean and the median of household *net* wealth increased from 1991 to 2006 and decreased after 2010. This reflects both the dynamics of house prices, which represents the main component of households' wealth, and the reduction in household disposable income and savings following the double-dip recession from 2008 to 2016 (Figure 4).[13]

Notably, as reported in Figure 5, a different dynamic has characterised households' financial wealth: the median has mostly progressively declined, reaching in 2016 about the 60% of the level of the beginning of the 1990s; the mean peaked in 2000 and declined over the next four years, stabilising in the following years at slightly higher values than the initial level.

These results suggest a different evolution of inequality when analysing net wealth and financial wealth. In the period 1991–2016, the Gini index of wealth has risen only slightly, while that of the financial component of wealth, already higher, has further increased (Figure 6). Thus, while Italian households' holdings of financial assets have become more skewed over time, the rise in inequality in total wealth is more muted.

This is underscored in Table 4, which decomposes the Gini index of household net wealth into its components. It is evident that the main driver of the increase in inequality is the financial component. Inequality in financial wealth has risen over time together with its absolute and percentage contribution to overall wealth inequality.

These data allow us to observe some preliminary evidence in favour of the Matthew effect for Italian households. Households with wealth in the top quartile of the distribution have consistently saved a larger share of their income, and this dispersion has even increased since 1991 (see Figure 7).[14] Moreover, these households received consistently higher returns on their investments than other wealth quartiles over the whole sample period (see Figure 8), probably due to more complex and risky assets and the aforementioned more efficient diversification of their portfolio. Table 5 shows average returns on financial wealth and associated standard errors by wealth quartile. With the exception of the bottom wealth quartile, where the variability of results are mainly due to the fact that only few households own financial assets, the coefficient of variation shows that higher returns are

[12] On the structure of the Italian households' portfolios, and on the causes of its poor diversification, see, among the others, Guiso and Jappelli (2002) and Brunetti and Torricelli (2010).

[13] Brandolini et al. (2018) discuss in detail the consequences of the double dip recession on households' income distribution, pointing out that the reduction in income has been pervasive across all social classes and accompanied by a reduction in both consumption and savings.

[14] The higher savings rate, or lower propensity to consume out of wealth, is consistent with evidence from other countries. For example, for France, see Arrondel et al. (2019).

associated with higher volatility and therefore higher risk. It should be noted that financial returns in the SHIW are estimated by applying fixed rates of return to the stock of different types of assets that the household reported to own at the end of the year (see Annex A). This estimation method reproduces a variability of returns that is in principle underestimated, as it can only be attributed to differences in the composition of the households' portfolios, rather than yield differences for the same type of securities. Nonetheless, it is able to generate a heterogeneity in the data quite close to what could be obtained using administrative data, outperforming other survey collection methods.[15]

With respect to fintech adoption, those households that use remote banking connections (less than 1% of respondents in 1991, and more than 25% in 2016) have also achieved higher returns than those who do not use such services (see Figure 9). This is consistent with evidence that remote banking has allowed households to increase participation in financial markets (Michelangeli and Viviano, 2020). Our first-pass analysis suggests that wealthier households may be in a better position to access higher-return financial products, including through remote banking, and that this, too, may be a factor in greater accumulation of wealth over time.

Figure 10 shows financial returns for households in municipalities with a number of bank branches equal to or higher than the national mean value in each year. Their returns are on average always higher. This provides further preliminary evidence that financial development may go hand in hand with higher financial returns for wealthier households.

Finally, it is interesting to note that, for the full period (i.e. using the whole sample and pulling all the years together), the correlation between the number of bank branches and the use of remote banking is weak and negative (about -5%). While the number of bank branches has shown an inverted U-shaped dynamic, the latter have progressively increased over time. Yet if we focus on single years, the correlation is always positive and significant, but with a change in the slope: it is mainly increasing until 2008 and then decreasing afterwards, when the two series have started to diverge (Figure 11).

4. Empirical framework

This section provides an empirical framework to study how financial development and fintech innovation could affect the process of wealth accumulation. In our baseline regressions we study the association of these two factors with the level of household financial wealth when controlling for a range of other factors. However, since the process of wealth accumulation also goes through the production of income, we examine the influence of financial development and fintech specifically on households' financial returns.

The baseline model specifications are the following:

$$FW_h = \alpha + \beta_1^{FW} FD_r + \beta_2^{FW} FT_h + \beta_3^{FW} FD_r * FT_h + \beta_4^{FW} X_h + \varepsilon_h \quad (1)$$

$$FR_h = \alpha + \beta_1^{FR} FD_r + \beta_2^{FR} FT_h + \beta_3^{FR} FD_r * FT_h + \beta_4^{FR} Y_h + \varepsilon_h \quad (2)$$

[15] For more details about the measurement of financial returns in the SHIW, also in comparison with other collection methods, see Gambacorta (2019).

where FW_h its financial wealth and FR_h the rate of financial returns. The covariates of interest are FD_r which denotes the financial development[16] and FT_h which represents the degree of fintech use of household h. These are, respectively, the number of branches in the province of residence r of the household in the survey year and a dummy 0/1 for use of remote banking connections. The models also contain the interaction of these two factors to investigate whether there is also a further combined effect on the dependent variables, i.e. whether they are substitutes ($\beta_3 < 0$) or complements ($\beta_3 > 0$).

The vector X_h contains a set of control variables. These include household demographics (age class, education, work status, area of birth of the head of the households, geographical area of residence), the household income class, and a dummy for the survey year. These variables are important, in particular given the potential correlation with variables such as financial literacy, and economic conditions. The vector of controls for the regression of financial returns, Y_h, is similar to that of the previous models, but wealth classes are used in place of income classes.

Both vectors X_h and Y_h include survey year dummies to capture the influence of aggregate (time series) trends, such as the decline in interest rates.

The descriptive evidence so far has highlighted that financial development and fintech use may have favoured the accumulation of wealth differently for various household wealth classes. To study this hypothesis more rigorously, we use quantile regressions, first proposed by Koenker and Basset (1978). This approach allows us to observe the effects of FD, FT and their interaction at different points of the dependent variable's conditional distribution. This method is particularly suited when dealing with highly skewed variables, such as wealth and in particular its financial component.[17]

In general, the conditional quantile regression can be defined as follows:

$$Q_K(\tau/Z) = \alpha(\tau) + \beta(\tau)Z + F_\varepsilon^{-1}(\tau)_h$$

where $Q_K(\tau/Z)$ is the conditional quantile function of the variable K at quantile τ given the set of covariates of the model (Z) and F_ε is the common distribution function of the errors. In particular, in this case, there will be different parameters' estimates, $\alpha(\tau)$ and $\beta(\tau)$, for each specified quantile τ, and this allows us to study how the effect of each variable varies when we move across the distribution of the outcome variable.

Using this approach, our models specifications become:

$$Q_{Fw}(\tau/Z) = \alpha^{FW}(\tau) + \beta_1^{FW}(\tau)FD_r + \beta_2^{FW}(\tau)TI_h + \beta_3^{FW}(\tau)FD_r * TI_h + \beta_4^{FW}(\tau)X_h + F_\varepsilon^{-1}(\tau)_h \quad (1')$$

$$Q_{FR}(\tau/Z) = \alpha^{FR}(\tau) + \beta_1^{FR}FD_r + \beta_2^{FR}(\tau)TI_h + \beta_3^{FR}(\tau)FD_r * TI_h + \beta_4^{FR}(\tau)Y_h + F_\varepsilon^{-1}(\tau)_h \quad (2')$$

[16] Financial development is expressed in terms of the number of branches in a province with respect to the population size (i.e. number of branches per 10,000 inhabitants). For the estimations, the variable has been standardised, i.e. transformed to have a mean of 0 and a standard deviation of 1.
[17] Quantile regression is more robust to outliers than least squares regression and avoids assumptions about the parametric distribution of the error process. For a more detailed description of the quantile regression method, see Koenker and Hallock (2001).

5. Endogeneity issues

One possible identification issue in testing the impact of financial development and financial technology on financial wealth is that household conditions could also impact on the distribution of bank branches and the use of remote banking. In particular, a given province could have a high branch density because banks have decided to open more branches to serve high-wealth clients in that province. Along similar lines, wealthy households may have easier access to remote banking, especially if access to the technology is particularly costly (e.g. requiring a computer or smartphone with a fast internet connection) or if it requires a high level of financial literacy. These issues could lead to endogeneity for both financial development and financial technology.

We have considered these issues by instrumenting the number of bank branches, the use of remote banking connections and their product (i.e. interaction). As an instrument for bank branches, we consider a lagged value, and more specifically the number of bank branches in 1989. This is highly correlated with the endogenous variable but it is only weakly correlated with the dependent variables.[18]

To address the potential endogeneity of remote banking, we have considered as an instrumental variable internet access in the territory, which is correlated with remote banking but not with the dependent variables. The available data on this in Italy are: (i) the share of households with internet access at home and (ii) the share of people that use the internet.[19] Unfortunately, data do not exist for the entire period of study. Rather, the two series are available since 2005 and 2001, respectively. In order to study the whole period of analysis, missing years have been estimated using a Tobit model with a lower bound equal to 0. The variable most correlated with the use of remote banking is represented by the share of people in the population using the internet, which has been chosen as the instrument for financial technology.[20]

Finally, we instrument the interaction between financial development and financial technology using the number of patents (per million inhabitants) registered in the European Patent Office (EPO), available from 1995 to 2012 (missing years have been estimated using a Tobit model).[21] The number of patents represents a standard measure of research productivity that is linked both to the presence of firms, and in general to economic activities, in the territory. This in turn is related to the number of bank branches. This instrument is also related to investment in innovation and to the development of technologies in general, such as online banking.

Endogeneity tests conducted using these instruments reject in all cases exogeneity for bank branches, remote banking usage, and their interaction. This underscores that IV estimation is needed to uncover causal effects on the process of accumulation of financial assets. Not taking into account this issue will lead to biased results: in principle, as both the financial development and fintech indicators used are positively associated to

[18] The correlation between the number of bank branches and its lagged value in 1989 is 0.70. The correlation with financial wealth and financial returns is 0.05 and 0.06, respectively.

[19] Instruments for remote banking connection have been downloaded by the Italian national statistical institute (ISTAT) website http://dati.istat.it.

[20] The correlation between remote banking and the share of people using internet is 0.31. The correlation with financial wealth and financial returns is 0.02 and -0.11, respectively.

[21] Source: Eurostat, available at http://www.istat.it/storage/politiche-sviluppo/Ricerca_innovazione_P.xls. The correlation between the number of patents and the interaction term is 0.17. The model also includes the instruments for bank branches and remote connection to banks.

financial wealth and its returns, this could probably lead to an overestimation of their impact and of their interaction. (This will be confirmed below).

6. Results

Tables 6 and 7 report the parameter estimates, respectively for households' financial wealth and the rate of financial returns as outcome variables, using IV OLS and IV quantile regressions for selected quantiles (10^{th}, 50^{th} and 90^{th} percentiles). Figures 12 and 13 report the corresponding estimated parameters, with confidence intervals, over the entire distribution of the dependent variables and for the relevant factors.

Considering first the entire period (panel A of Table 6 and Figure 12), results show that both financial development (FD)[22] and financial technology (FT) have a positive effect on households' financial wealth. This effect is present for all wealth quintiles, but it increases starkly when moving toward the top of the distribution. For the wealthiest households, a one-standard deviation increase in the number of bank branches is associated with financial wealth that is €33,000 higher, ceteris paribus. For these households, access to remote banking is associated with financial wealth that is about €4,000 higher. The interaction of the two factors is negative and significant, which implies that bank branches and digital banking applications can be considered as substitutes. A household with both a one-standard deviation increase in bank branches *and* remote banking has financial wealth that is €34,000 higher – less than the sum of the two effects. The positive effects of digital banking on financial wealth and financial return increase when banks downsize their physical operations. This matches with the result that customer's distance to a physical banking location is becoming less important in the age of digital banking (Choi and Loh, 2019).[23] The topic of closures of physical banking locations in the US has also been recently examined by Nguyen (2019).

As far the rate of financial returns, most of the abovementioned results are confirmed (panel A of Table 7 and Figure 13). Again, in both the IV OLS and quintile regressions, there is a positive effect of FD and FT, and a negative effect of their interaction in all quantiles. For upper-class, middle-class and lower-class households (as defined by wealth and returns), wealth and yields are thus higher given access to more bank branches or remote banking, but there are declining benefits from having access to both. Yet both effects are concentrated among the wealthiest households. For the wealthiest households, a one-standard deviation increase in bank branches is associated with returns that are 2.70 percentage points higher (roughly one standard deviation). With remote banking, wealthy households earn returns that are 0.28 percentage points (28 basis points) higher. With access to both, returns are 2.75 percentage points higher.

We next use the financial technology indicator to split the sample into two periods. The first characterised is by a low level of remote banking diffusion among households (1991–

[22] As the number of bank branches has been standardised (i.e. transformed to have a mean of 0 and standard deviation of 1), a change of one point in the corresponding variable can be interpreted as to one-standard error variation.

[23] Using quasi-exogenous closures of ATMs in a densely populated city-state (Singapore), Choi and Loh (2019) examine how small frictions to physical banking access can affect digital banking adoption. They find that after such closures, affected customers' travel distances to ATMs increase. This induces them to increase their usage of the bank's digital platform.

2002) and the second by an increasingly higher level of remote banking use (2004–2016). Results using these two sub-periods are reported respectively in panel B and C of the aforementioned table and figures. With respect to both financial wealth and financial returns, the results are consistent in both periods. Yet the economic magnitude of the effects is much larger in the first period considered. Specifically, for households in the top decile of the distribution in 1991–2002, a one standard deviation increase in FD is associated with an increase by 9.330 percentage points in the rate of returns on financial assets (equivalent to 1.7 standard deviations in the rate of returns). Having access to remote banking has an effect of 0.80 percentage points. In the second period (from 2004 to 2016), for the same households, financial development will increase returns by only 0.83 percentage points and remote banking access by 0.12 (i.e. 12 basis points).

Another way to track changes over time is to estimate our model for each individual wave of the SHIW over the sample period. As the diffusion of remote connection to banks in Italy significantly started in 1995, we dropped the first two waves. Figures 14 and 15 give the coefficients for financial wealth and the rate of return on financial wealth from our IV OLS estimation over the full period. In each case, the effects of FD, FT and their interaction were largest around the 1998 wave, and have subsequently declined. While the coefficients are statistically significant throughout, their economic magnitude falls. These conclusions are confirmed by the IV quantile regressions by survey wave, reported in Figures 16 and 17, showing that the coefficients for the wealthiest households tend to decline over time.

These results show clearly that the effect of financial technology, also in combination with financial development, becomes less relevant for the accumulation of financial wealth in the latter half of our sample, after 2004. As remote banking and other fintech innovations have become more widely adopted, it seems that the scale of benefits – in terms of higher returns and hence the possibility of greater accumulation over time – has declined. This may mean that the broader diffusion of technology has decreased the benefits to the wealthy.

7. Robustness checks and extensions

The robustness of the results has been checked in several ways. The first test is to compare the results of the IV regressions with those of the corresponding models not corrected for endogeneity, i.e. simple OLS and quantile regressions, we can observe that the bias due to endogeneity is extremely relevant for the interaction term. In particular, in a standard OLS model (reported in Annex C) the coefficients of the interaction are always positive and significant, while they are negative and significant when instrumental variables are considered. There is thus a strong upward bias in the interaction term parameter due to endogeneity issues. Since both financial development and fintech are positively associated with wealth, not taking into account the endogeneity issue properly would lead to a reinforcement of the effect of the interaction – implying that fintech and financial development are complements, whereas we find them to be clear substitutes.

An additional check is to run the regressions with bank-specific characteristics as additional control variables. The "bank lending channel" literature typically identifies loan supply shocks by claiming that certain bank-specific characteristics (e.g. size, liquidity, capitalisation) influence only loan supply movements, while banks' loan demand is independent of them. For example, after a negative shock, the drop in the supply of credit should be larger for small banks, which are financed almost exclusively from deposits and equity (Kashyap and Stein, 1995); for less liquid banks, which cannot protect their loan portfolio against monetary tightening simply by drawing down cash and securities (Stein, 1998; Kashyap and Stein, 2000); and for poorly capitalised banks, which have less access to markets for uninsured funding (Kishan and Opiela, 2000; Gambacorta and Shin, 2018). In our data, a good matching with bank-specific characteristics is possible only from 2004. The regression results for the period 2004–2016, reported in Annex D, are qualitatively very similar to those in Tables 6C–7C and Figures 11C–12C. We can thus conclude that our results are robust to the inclusion of bank-specific characteristics.

In a final test, we focus on the riskier components of financial assets. In particular, we have pooled in a category of "risk-bearing financial assets" bonds, investment funds and equity shares. The results reported in Annex E are even more concentrated among the wealthiest households, with no effect below the 90th percentile of the distribution. We report an additional column in Table E.1 for effects above the 95th percentile. It is worth mentioning that only considering stock market wealth would lead to even more skewed results due to the scarce diffusion of these assets among Italian households (see Table 3).

8. Conclusions

This paper has presented evidence on the nexus between financial development, financial technology and inequality in (returns to) wealth. Using Italian household data, we show first that wealthier households have consistently achieved higher returns; thus, we document the Matthew effect. Moreover, we find that both financial development and fintech are tied to higher financial wealth and in financial returns. While households of all wealth deciles benefit, these benefits increase starkly moving toward the top of the wealth distribution – particularly the top decile. In other words, financial development and fintech may contribute to inequality and the broader Matthew effect.

Still, this mechanism has changed in the latter years of our sample, as the use of fintech and the internet among Italian households has progressively risen. While the effect of both financial development (bank branches) and financial technology (remote banking) on financial wealth and the rate of returns on financial wealth are very strong and significant in the first part of the estimation period (1991–2002), the economic significance is smaller in the second period (2004–2016). Thus, the gap between the wealth and the rest that is attributable to financial development and fintech has fallen as bank branches declined and remote banking became more widely diffused. This and other results are further supported by additional tests.

While this study can only present data for Italy, an advanced economy with a bank-based financial system, it sheds further light onto mechanisms that may be more broadly applicable. In elucidating one driver of differential returns to wealth, this research can help to understand the forces behind wealth inequality, and potentially the necessary policy responses.

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Figures and Tables

Figure 1

Remote banking connection by geographical area over time (1995–2016)

(percentages of households)

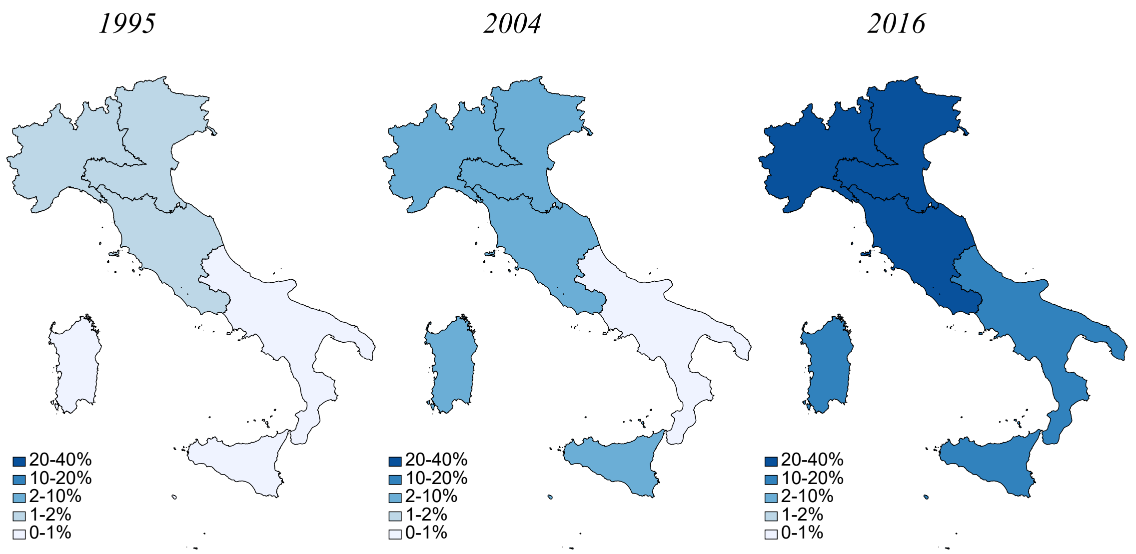
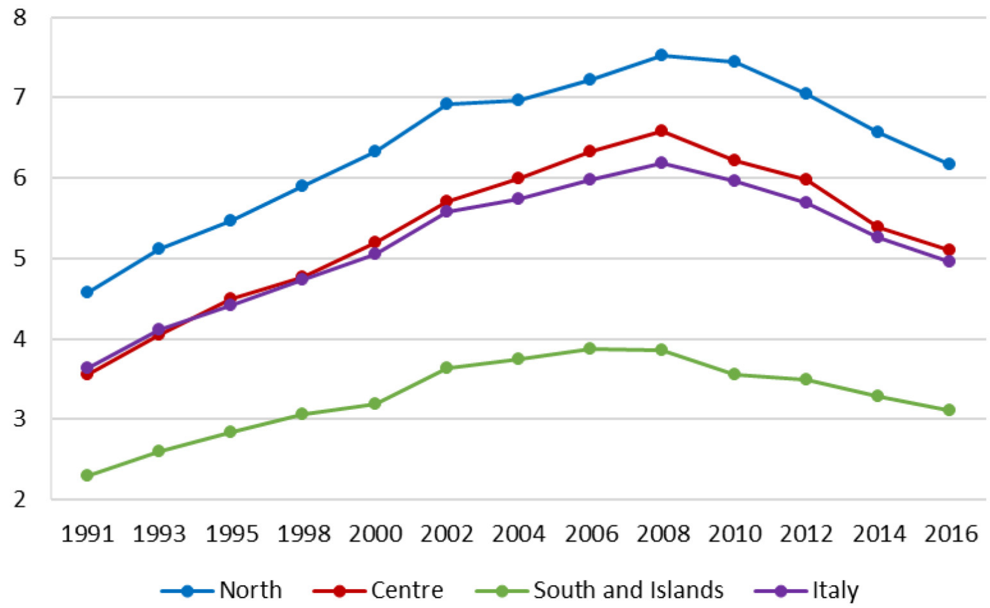


Figure 2

Bank branches by geographical area (1991–2016)

(number of bank branches per 10,000 inhabitants)

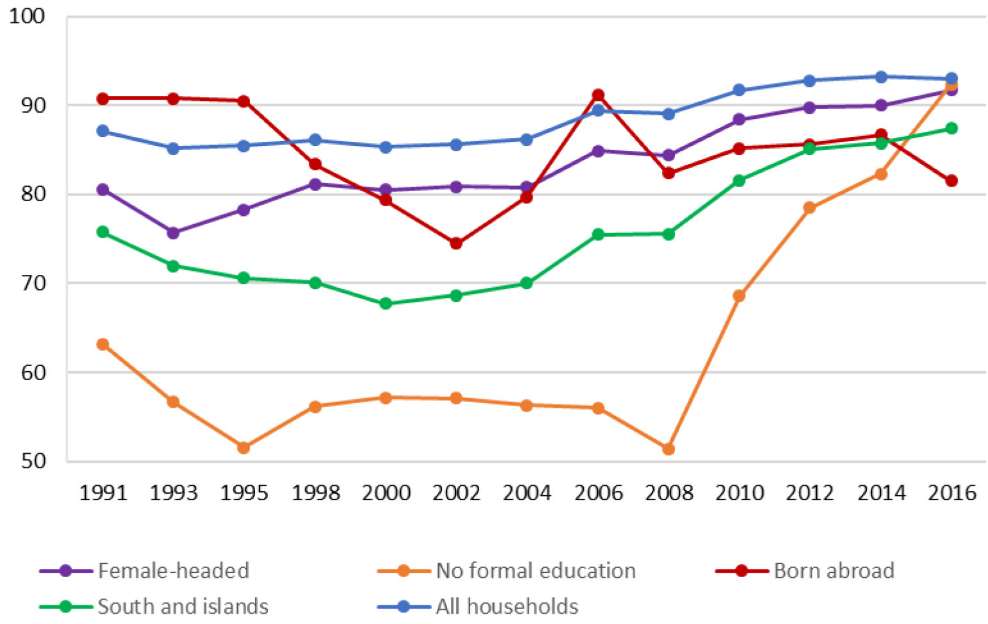


Source: authors' calculations on SHIW HA 10.1.

Figure 3

Holding of bank and post office accounts by groups of households (1991–2016)

(in percent)

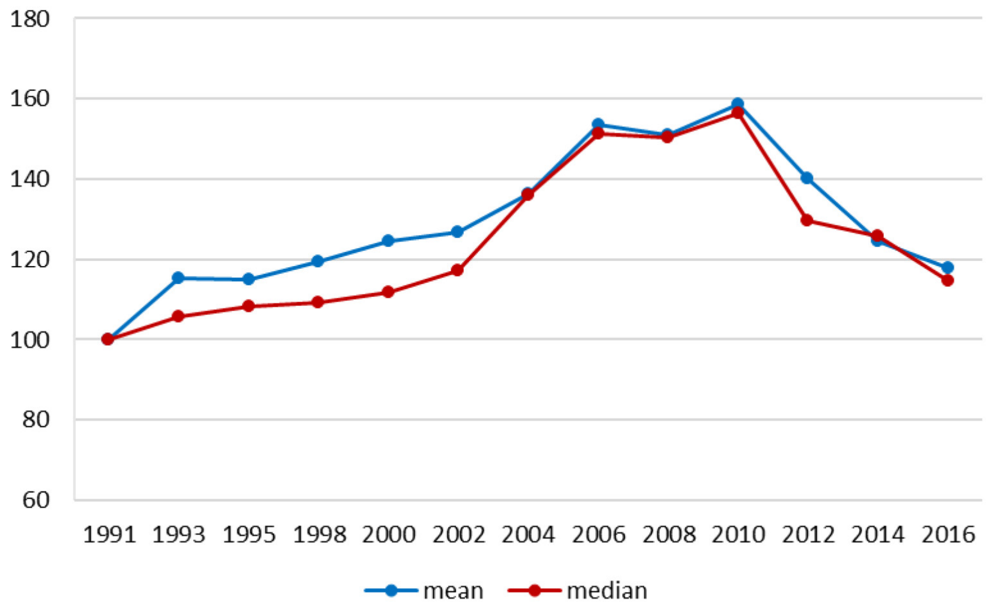


Source: authors' calculations on SHIW HA 10.1.

Figure 4

Net household wealth (1991–2016)

(index, 1991=100)

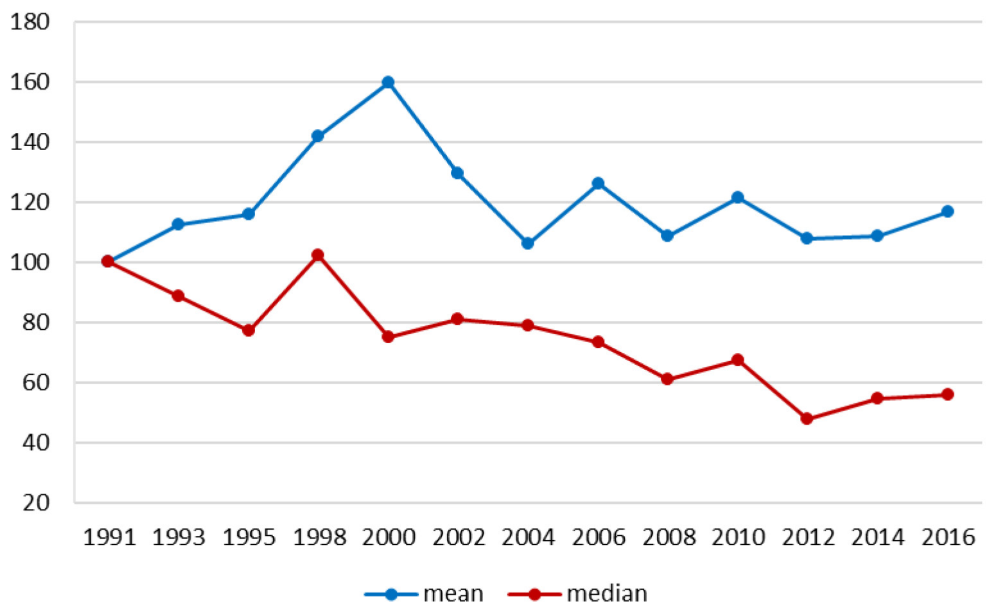


Source: authors' calculations on SHIW HA 10.1.

Figure 5

Household financial wealth (1991–2016)

(index, 1991=100)

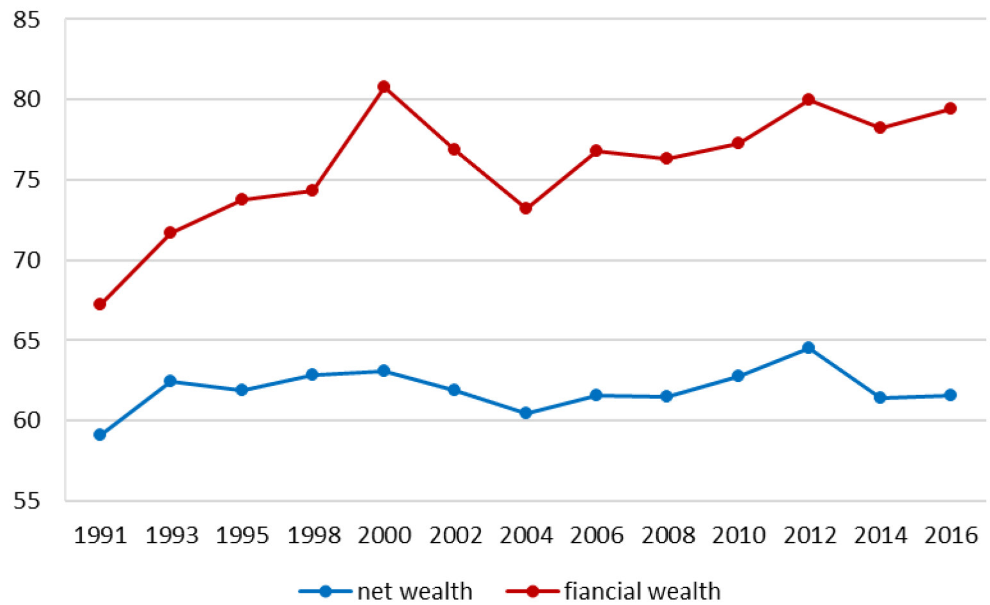


Source: authors' calculations on SHIW HA 10.1.

Figure 6

Gini index for household net wealth and financial wealth (1991–2016)

(percentages)

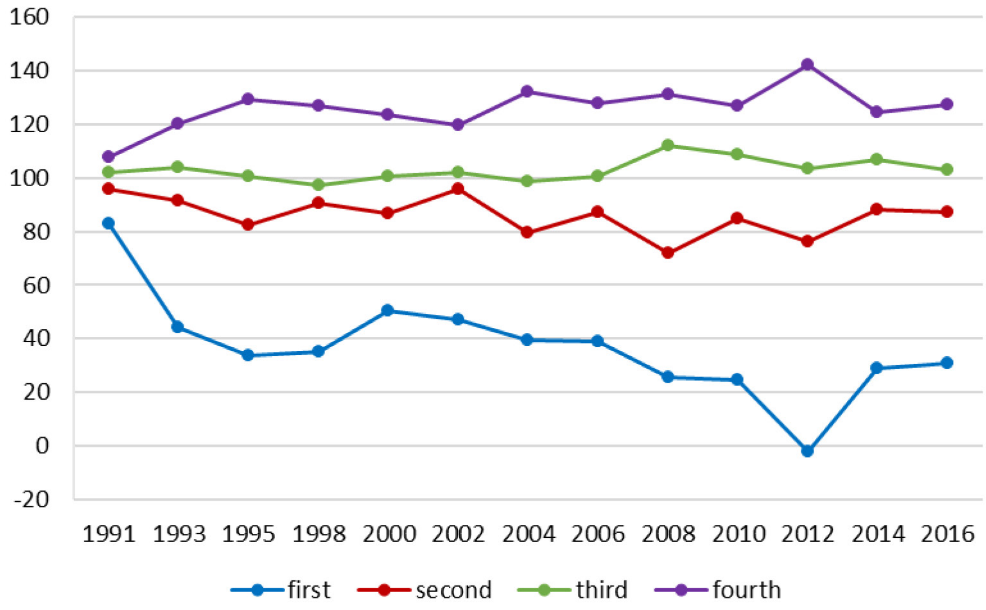


Source: authors' calculations on SHIW HA 10.1.

Figure 7

SHIW saving rates[1] by net worth quartile (1991–2016)

(index, average of the year=100)

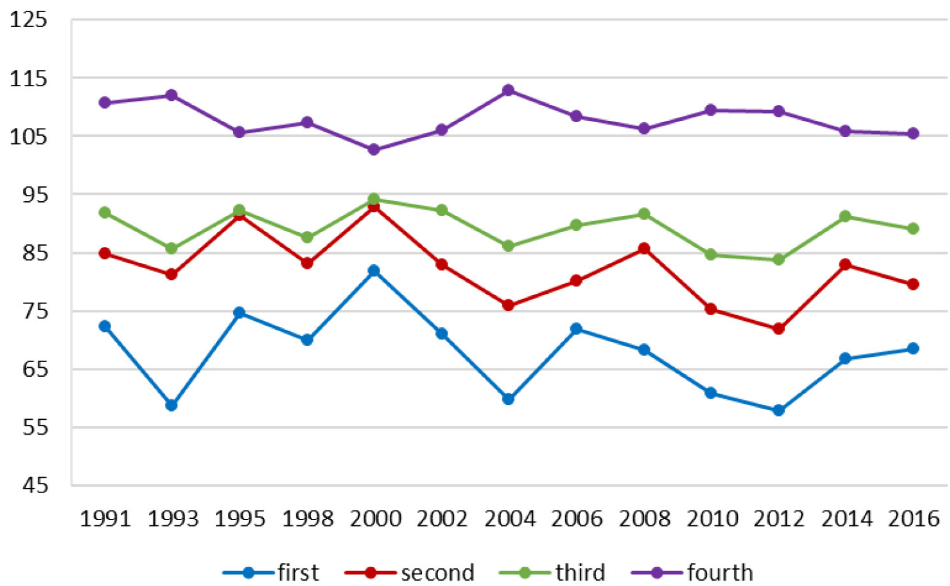


Note: (1) savings computed as a residual of (income less consumption). Source: authors' calculations on SHIW HA 10.1. Values relative to the average.

Figure 8

SHIW rates of financial returns[1] by net worth quartile (1991–2016)

(index, average of the year=100)

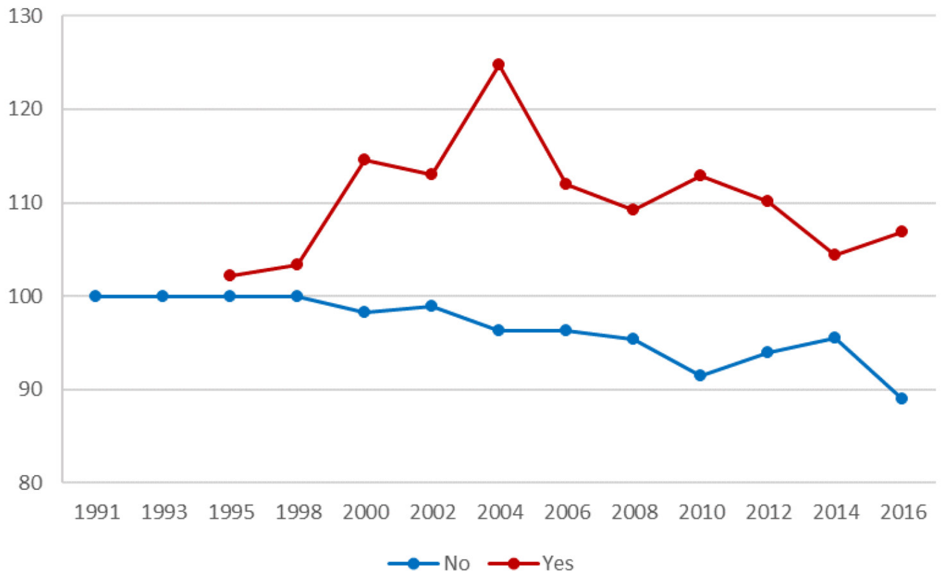


Note: (1) rates of financial returns are obtained as the ratio between the mean financial returns and the mean level of financial asset in each net worth quartile (financial wealth only includes assets to which a yield has been attached). Source: authors' calculations based on SHIW HA 10.1. Values relative to the average.

Figure 9

SHIW rates of financial returns[1] by remote banking use[2] (1991–2016)

(index, average of the year=100)



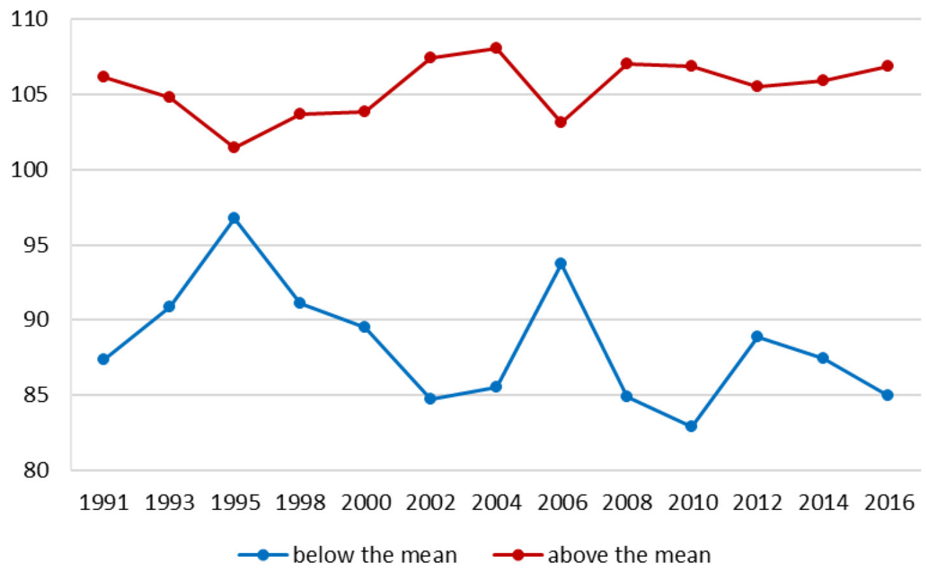
Note: (1) see Figure 8; (2) Online banking use is the answer to the question: "Did you or a member of the household do business with banks or financial intermediaries by telephone or computer in the last calendar year (home banking, online account, ...)?". Source: authors' calculations based on SHIW HA 10.1.

Figure 10

SHIW rates of financial returns[1]

by number of bank branches in the province of residence

(index, average of the year=100)

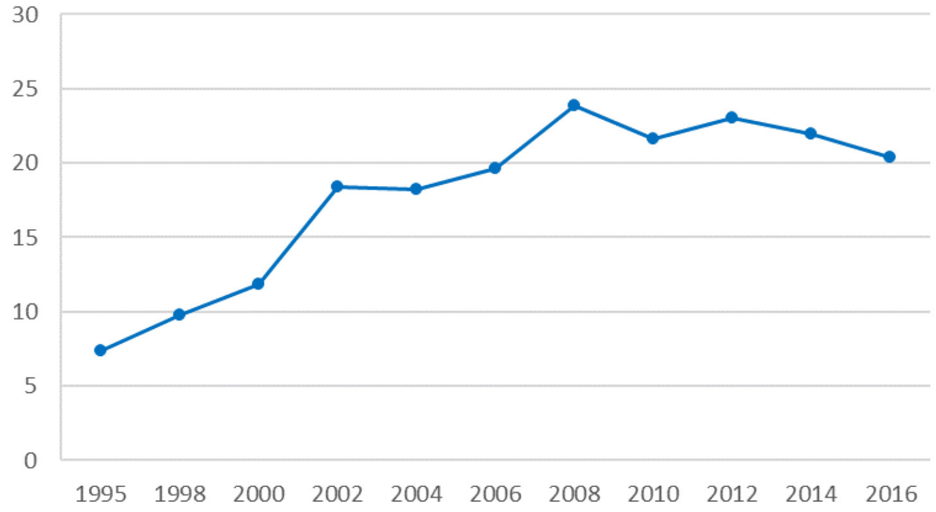


Note: (1) see Figure 8; Source: authors' calculations on SHIW HA 10.1. Values relative to the average.

Figure 11

Pearson correlation between the use of remote banking and number of bank branches in the province of residence

(percentages)



Source: authors' calculations on SHIW HA 10.1.

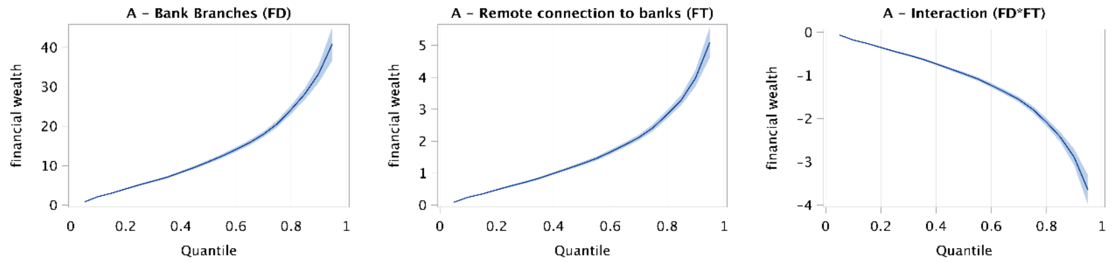
Figure 12

IV estimated parameters by quantile for household financial wealth

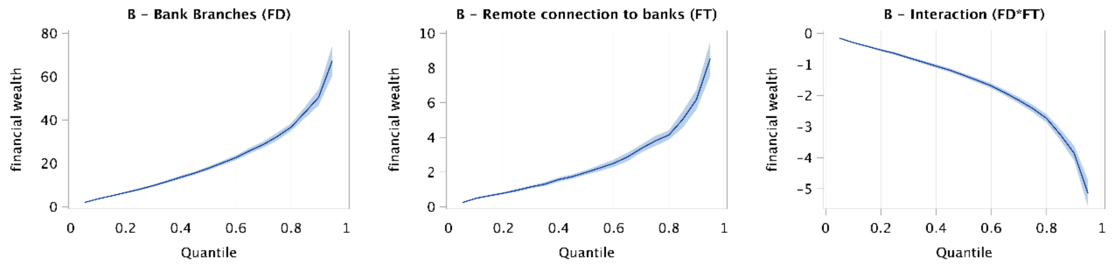
(thousands of 2016 euros)

Bank Branches (FD) (standardised) | *Remote connection to banks (FT)* | *Interaction (FD*FT)*

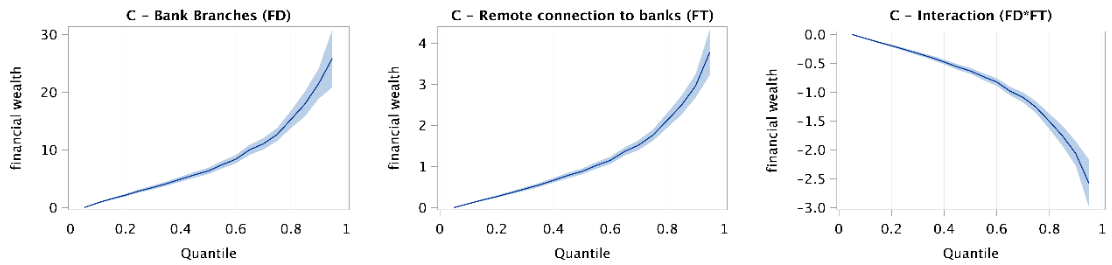
A - Total sample (1991–2016)



B - First period (1991–2002)



C - Second period (2004–2016)



Source: authors' calculations on SHIW HA 10.1. Weighted IV quantile regressions. Estimate parameters for specific covariates by quantile levels of household financial wealth. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household income and survey year (individual characteristics refer to the head of household, i.e. the member with the highest income). Quantile levels of household financial wealth on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

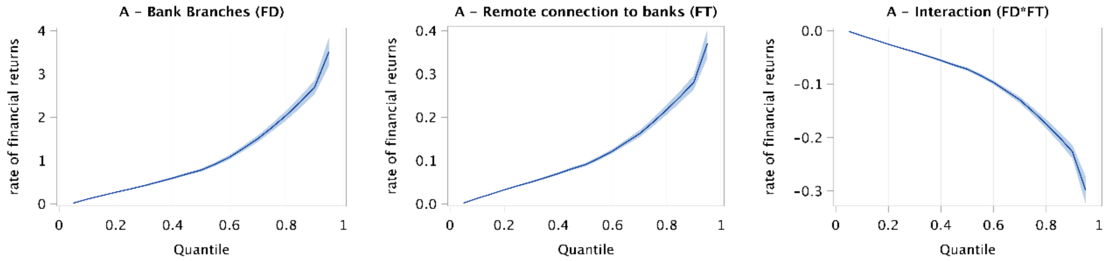
Figure 13

IV estimated parameters by quantile for household rate of financial returns

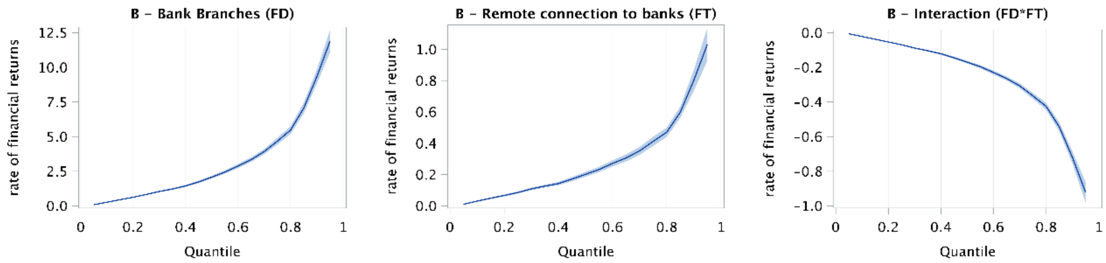
(percentages)

Bank Branches (FD) (standardised) *Remote connection to banks (FT)* *Interaction (FD*FT)*

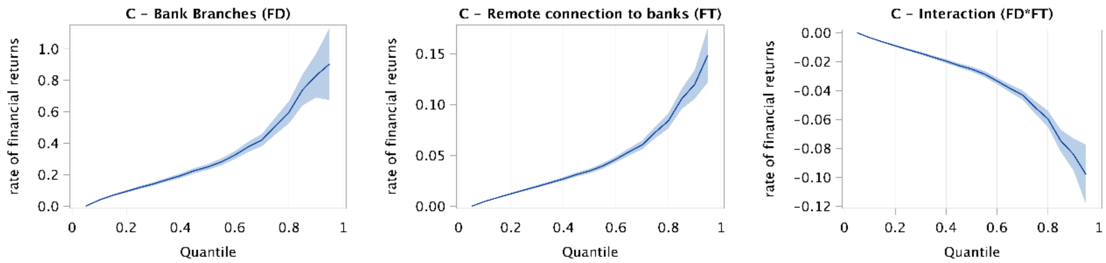
A - Total sample (1991–2016)



B - First period (1991–2002)



C - Second period (2004–2016)

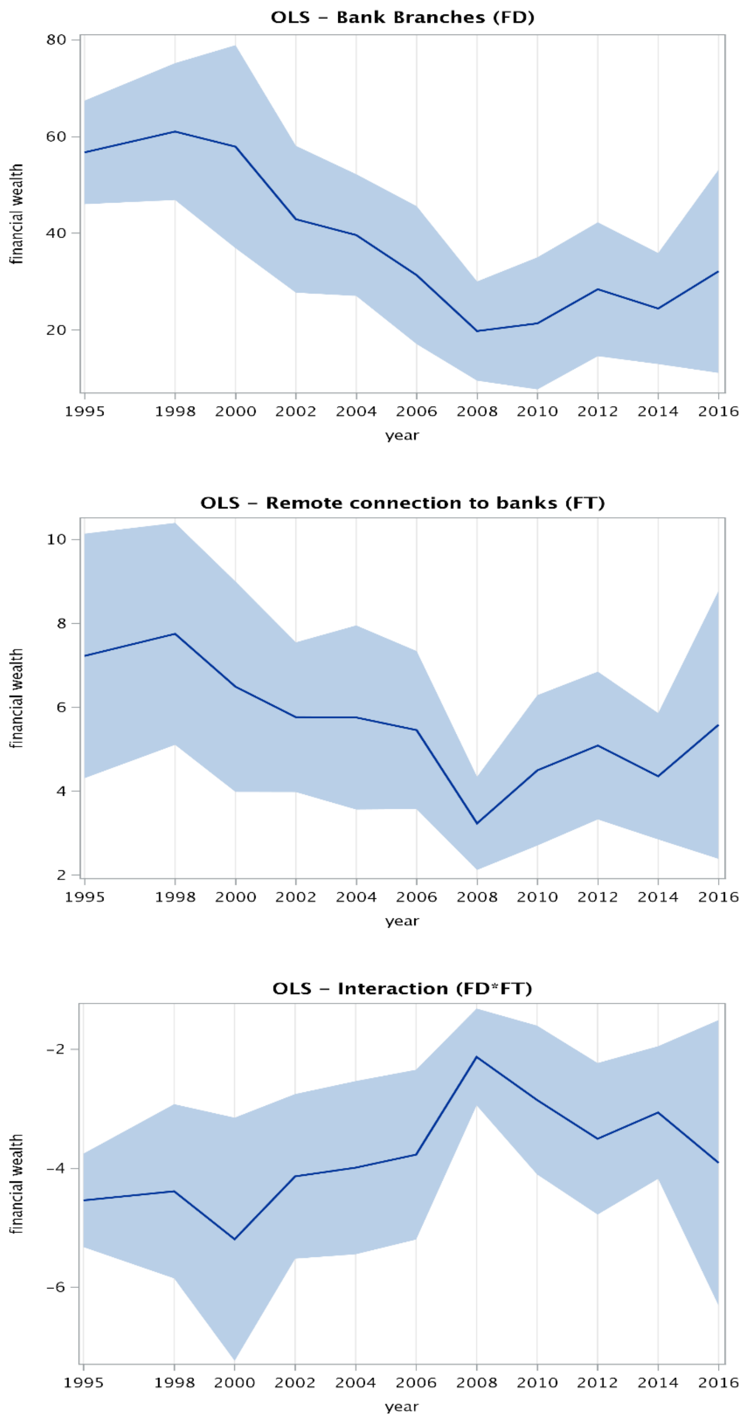


Source: authors' calculations on SHIW HA 10.1. Weighted IV quantile regressions. Estimate parameters for specific covariates by quantile levels of household rate of financial returns. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household wealth and survey year (individual characteristics refer to the head of household, i.e. the member with the highest income). Quantile levels of household rate of financial returns on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

Figure 14

IV OLS Estimated parameters by survey year for household financial wealth

(thousands of 2016 euros)

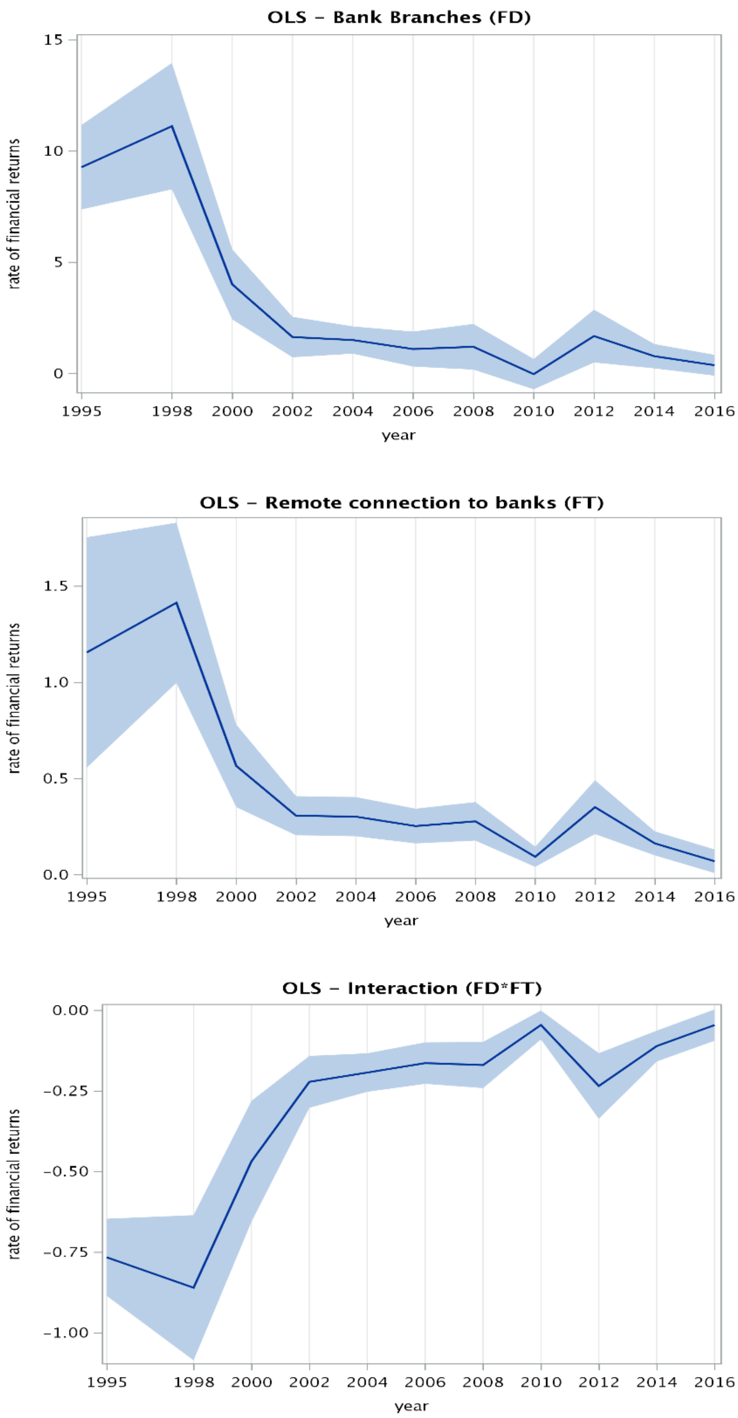


Source: authors' calculations on SHIW HA 10.1. Estimate parameters for specific covariates in weighted OLS IV regressions for household financial wealth on the vertical axis. Survey year on the horizontal axis. 95% confidence intervals shown by a blue band. Other covariates: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household income (individual characteristics refer to the head of household, i.e. the member with the highest income).

Figure 15

IV OLS Estimated parameters by survey year for household financial returns

(percentages)

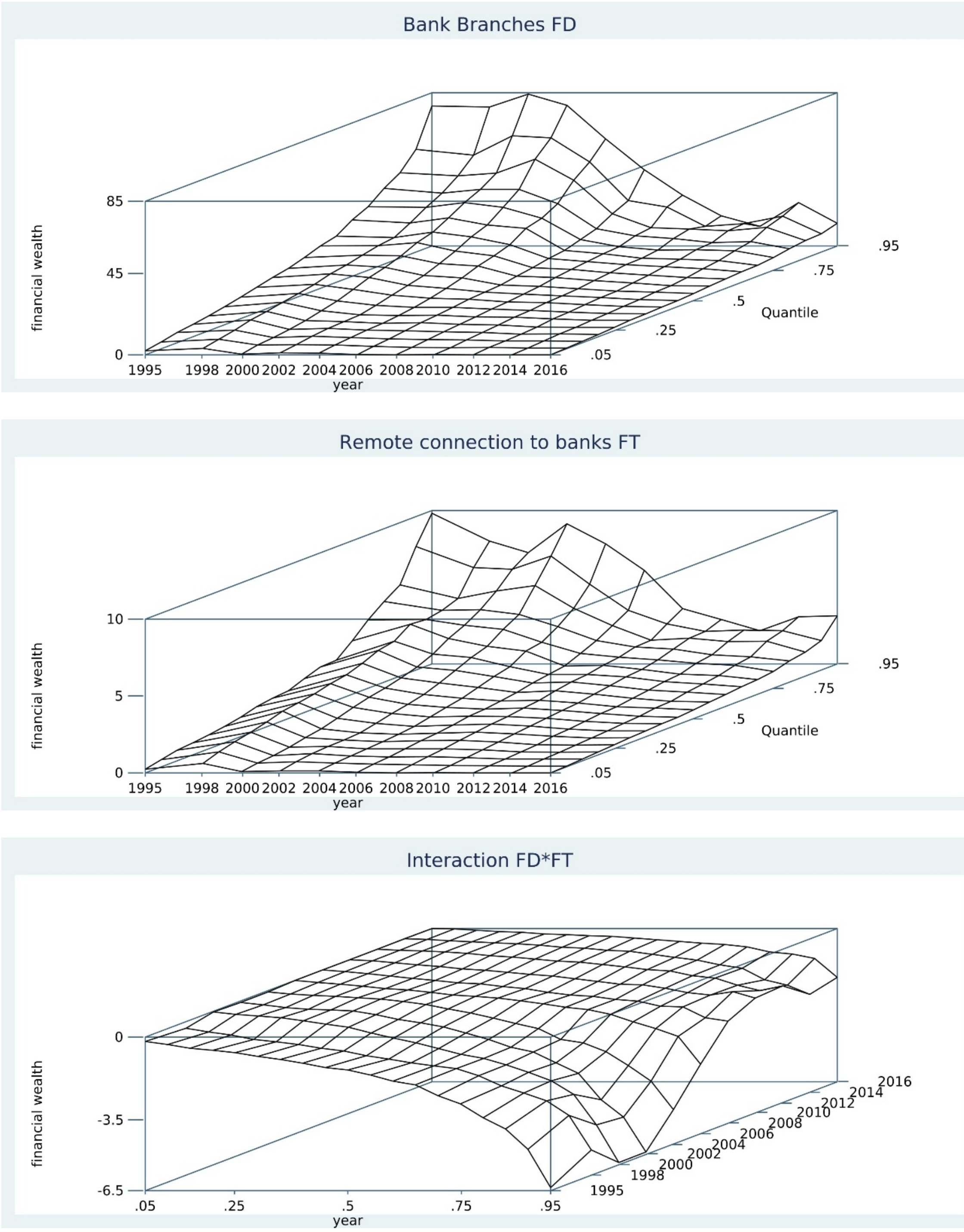


Source: authors' calculations on SHIW HA 10.1. Estimate parameters for specific covariates in weighted OLS IV regressions for household financial returns on the vertical axis. Survey year on the horizontal axis. 95% confidence intervals, shown by a blue band. Other covariates: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household wealth (individual characteristics refer to the head of household, i.e. the member with the highest income).

Figure 16

IV quantile estimated parameters by survey year for household financial wealth

(thousands of 2016 euros)

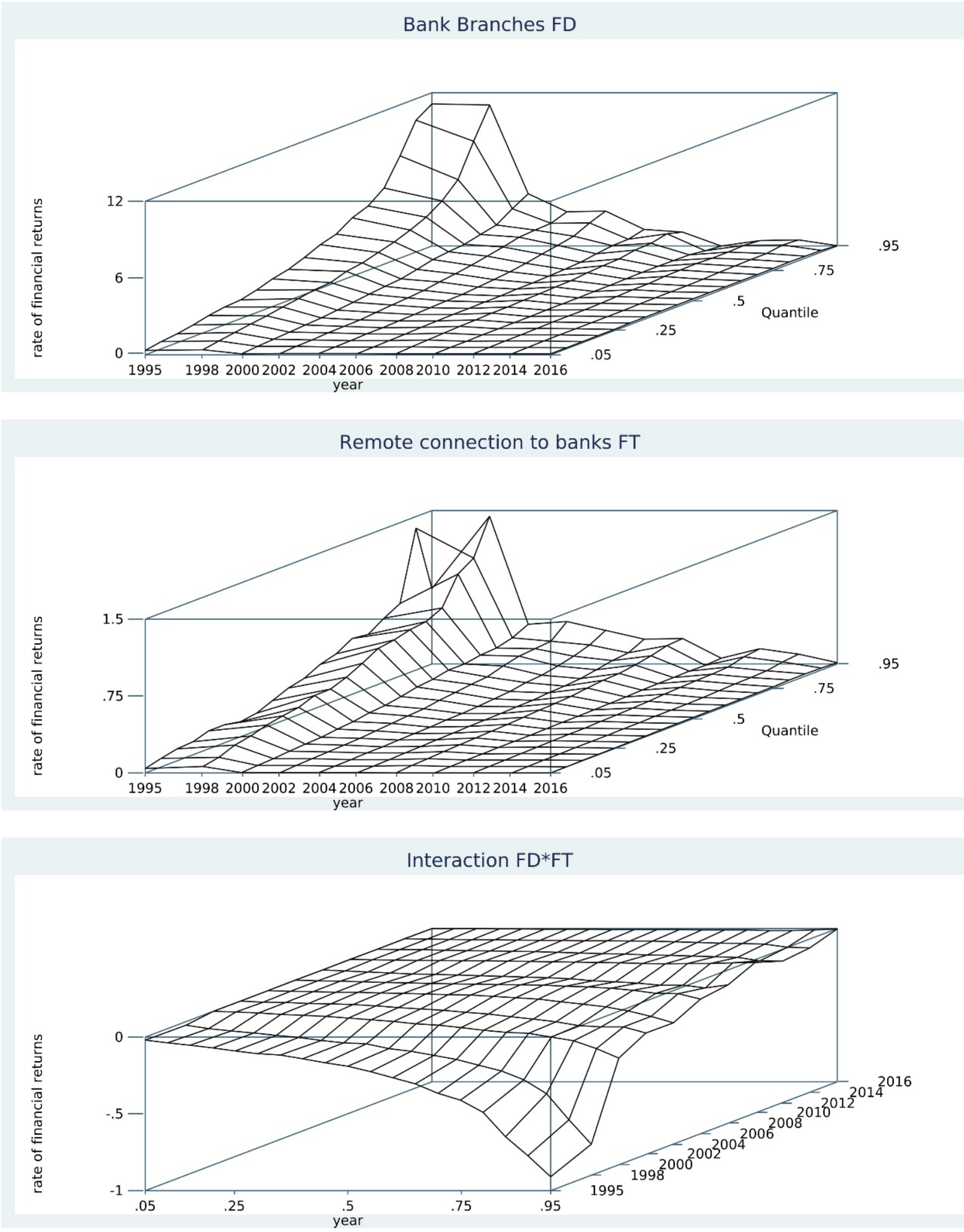


Source: authors' calculations on SHIW HA 10.1. Weighted IV quantile regressions. Estimate parameters for specific covariates by quantile levels of household financial wealth and by survey year. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household income (individual characteristics refer to the head of household, i.e. the member with the highest income).

Figure 17

IV quantile estimated parameters by survey year for rate of financial returns

(percentages)



Source: authors' calculations on SHIW HA 10.1. Weighted IV quantile regressions. Estimate parameters for specific covariates by quantile levels of household rate of financial returns and by survey year. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household wealth (individual characteristics refer to the head of household, i.e. the member with the highest income).

Table 1

Summary statistics household-level variables (1991–2016)

(thousands of 2016 euro, percentages of households)

Variable[1]	Mean	Std. Dev.	10th pct	Median	90th pct
Net wealth	226.8	432.5	1.9	133.4	504.7
Financial assets	28.4	101.9	0.0	7.6	61.0
Rate of financial returns	2.3	5.3	0.0	1.4	4.8
Bank branches (FD)[2]	5.2	2.0	2.6	5.1	7.9
Remote connection to banks (FT)	10.0	30.1	0.0	0.0	100.0
Gender					
Male	68.9	46.3	0.0	100.0	100.0
Female	31.1	46.3	0.0	0.0	100.0
Age class					
up to 30 years	7.7	26.6	0.0	0.0	0.0
from 31 to 40 years	18.6	38.9	0.0	0.0	100.0
from 41 to 50 years	20.1	40.1	0.0	0.0	100.0
from 51 to 65 years	24.9	43.2	0.0	0.0	100.0
more than 65 years	28.8	45.3	0.0	0.0	100.0
Born abroad	5.1	22.0	0.0	0.0	0.0
Work Status					
Employed	45.8	49.8	0.0	0.0	100.0
Self-employed	13.0	33.6	0.0	0.0	100.0
Not employed	41.2	49.2	0.0	0.0	100.0
University degree	10.1	30.1	0.0	0.0	100.0
Geographical area					
North	48.0	50.0	0.0	0.0	100.0
Centre	19.7	39.7	0.0	0.0	100.0
South and islands	32.4	46.8	0.0	0.0	100.0

Notes: ([1]) Individual characteristics refer to the head of household, i.e. the member with the highest income; ([2]) number of bank branches in the province of residence per 10.000 inhabitants. Number of observations: 103,007. All statistics use sample weights. Source: authors' calculations on SHIW HA 10.1. Survey years: 1991–2016.

Table 2

Households' net and financial wealth composition

(share of net wealth; percentages)

Survey year	Net wealth			Financial wealth		
	Financial wealth	Real wealth	Liabilities (-)	Deposits	Government securities	Other securities
1991	13.6	90.2	3.8	54.6	34.6	10.8
1993	13.3	90.6	3.8	46.8	34.8	18.3
1995	13.7	90.2	3.9	44.3	36.8	18.9
1998	16.1	87.7	3.9	49.8	12.5	37.7
2000	17.4	86.3	3.7	47.5	14.2	38.3
2002	13.9	89.6	3.5	55.6	10.3	34.2
2004	10.6	93.8	4.3	54.4	10.4	35.2
2006	11.2	93.3	4.5	53.7	11.5	34.8
2008	9.8	94.9	4.7	57.9	11.9	30.2
2010	10.4	94.3	4.8	52.3	11.1	36.6
2012	10.5	95.0	5.5	49.9	11.6	38.5
2014	11.9	92.8	4.7	52.0	12.1	35.9
2016	13.4	91.7	5.1	56.1	8.6	35.3

Source: authors' calculations on SHIW HA 10.1.

Table 3

Participation in financial asset components by net wealth decile

(share of households, percentages)

Net wealth decile	Deposits	Government securities	Bonds	Investment funds	Equity shares	Other securities
			1991			
1st	34.3	0.7	0.0	0.0	0.0	0.0
2nd	62.7	5.1	0.0	0.2	0.0	0.3
3rd	63.1	23.0	0.5	1.1	1.2	0.3
4th	46.5	15.7	0.8	1.2	1.2	0.1
5th	55.2	17.6	1.0	0.8	1.1	0.1
6th	65.5	23.6	1.4	0.8	2.2	1.4
7th	74.2	31.4	0.6	3.5	3.8	1.4
8th	78.4	33.4	1.5	1.8	3.7	1.7
9th	88.6	41.4	4.1	5.0	6.8	1.7
10th	91.1	47.4	5.6	9.4	14.2	2.5
			2016			
1st	57.8	0.0	0.0	0.2	0.0	0.0
2nd	86.8	0.0	0.0	0.0	0.0	0.3
3rd	87.7	2.4	2.3	3.0	1.0	1.2
4th	81.8	3.6	1.1	1.5	1.1	1.2
5th	89.4	3.0	2.5	2.1	0.6	1.5
6th	89.7	5.3	3.3	5.0	1.9	1.3
7th	89.9	7.1	4.0	6.5	1.3	2.5
8th	95.1	11.8	7.8	7.5	4.0	2.8
9th	98.2	10.4	10.0	14.7	7.6	4.5
10th	99.8	17.3	14.8	19.8	15.2	11.2

Source: authors' calculations on SHIW HA 10.1.

Table 4

Net wealth Gini index decomposition by factors

(percentages)

Year	Wealth component	Share in net worth	Gini index	Rank correlation ratio	Absolute contribution	Percentage contribution
1991	Real assets	90.2	61.0	97.6	53.7	90.8
	Financial assets	13.6	67.3	64.3	5.9	9.9
	Financial liabilities	3.8	92.1	13.2	0.5	0.8
	Net Worth	100.0	59.1	100.0	59.1	100.0
1993	Real assets	90.6	63.6	98.2	56.6	90.6
	Financial assets	13.3	71.7	72.3	6.9	11.0
	Financial liabilities	3.8	90.9	28.9	1.0	1.6
	Net Worth	100.0	62.4	100.0	62.4	100.0
1995	Real assets	90.2	62.9	98.3	55.8	90.1
	Financial assets	13.7	73.7	74.6	7.5	12.2
	Financial liabilities	3.9	90.8	40.2	1.4	2.3
	Net Worth	100.0	61.9	100.0	61.9	100.0
1998	Real assets	87.7	63.8	98.1	54.9	87.3
	Financial assets	16.1	74.3	79.7	9.5	15.2
	Financial liabilities	3.9	93.6	44.0	1.6	2.5
	Net Worth	100.0	62.9	100.0	62.9	100.0
2000	Real assets	86.3	62.8	97.7	53.0	83.9
	Financial assets	17.4	80.8	82.7	11.6	18.4
	Financial liabilities	3.7	92.5	42.9	1.5	2.3
	Net Worth	100.0	63.1	100.0	63.1	100.0
2002	Real assets	89.6	62.0	98.0	54.4	87.9
	Financial assets	13.9	76.9	78.9	8.4	13.6
	Financial liabilities	3.5	92.4	29.9	1.0	1.6
	Net Worth	100.0	61.9	100.0	61.9	100.0
2004	Real assets	93.8	60.8	98.4	56.1	92.8
	Financial assets	10.6	73.2	72.5	5.6	9.3
	Financial liabilities	4.3	92.1	31.0	1.2	2.1
	Net Worth	100.0	60.5	100.0	60.5	100.0
2006	Real assets	93.3	61.5	98.1	56.3	91.5
	Financial assets	11.2	76.8	75.3	6.5	10.5
	Financial liabilities	4.5	92.6	29.0	1.2	2.0
	Net Worth	100.0	61.6	100.0	61.6	100.0
2008	Real assets	94.9	60.8	98.3	56.8	92.3
	Financial assets	9.8	76.3	75.3	5.6	9.1
	Financial liabilities	4.7	90.7	21.3	0.9	1.5
	Net Worth	100.0	61.5	100.0	61.5	100.0
2010	Real assets	94.3	62.0	98.2	57.4	91.5
	Financial assets	10.4	77.3	77.4	6.2	9.9
	Financial liabilities	4.8	91.0	21.0	0.9	1.5
	Net Worth	100.0	62.7	100.0	62.7	100.0
2012	Real assets	95.0	63.4	98.1	59.1	91.7
	Financial assets	10.5	80.0	77.5	6.5	10.1
	Financial liabilities	5.5	91.7	22.1	1.1	1.7
	Net Worth	100.0	64.5	100.0	64.5	100.0
2014	Real assets	92.8	60.3	97.8	54.7	89.2
	Financial assets	11.9	78.2	77.7	7.2	11.8
	Financial liabilities	4.7	91.9	13.0	0.6	0.9
	Net Worth	100.0	61.4	100.0	61.4	100.0
2016	Real assets	91.7	60.7	97.6	54.3	88.2
	Financial assets	13.4	79.4	81.1	8.7	14.1
	Financial liabilities	5.1	93.5	28.7	1.4	2.2
	Net Worth	100.0	61.6	100.0	61.6	100.0

Source: authors' calculations on SHIW HA 10.1.

Table 5

Household rate of returns by net wealth quartile (1991–2016)

(percentages)

Net wealth quartile	Average	Standard deviation	Coefficient of variation
1st	1.6	4.2	269.0
2nd	2.0	2.8	137.3
3rd	2.4	4.6	189.0
4th	3.1	7.8	255.0

Table 6

IV OLS and IV quantile regression parameters for household financial wealth

(thousands of 2016 euro)

Characteristics[1]	IV OLS	P10	P50	P90
A - Total sample (1991–2016) [2]				
Bank branches (FD) (standardised)	35.547***	2.129***	10.951***	33.237***
	(1.925)	(0.061)	(0.240)	(1.134)
Remote connection to banks (FT)	5.121***	0.243***	1.289***	3.973***
	(0.260)	(0.007)	(0.028)	(0.132)
Interaction (FT*FD)	-3.618***	-0.183***	-0.962***	-2.894***
	(0.187)	(0.005)	(0.020)	(0.096)
B - First period (1991–2002) [3]				
Bank branches (FD) (standardised)	44.595***	3.66***	17.729***	50.401***
	(2.849)	(0.103)	(0.425)	(1.906)
Remote connection to banks (FT)	5.583***	0.486***	1.982***	6.172***
	(0.411)	(0.021)	(0.070)	(0.291)
Interaction (FT*FD)	-3.769***	-0.302***	-1.352***	-3.861***
	(0.260)	(0.008)	(0.033)	(0.122)
C - Second period (2004–2016) [4]				
Bank branches (FD) (standardised)	28.296***	0.836***	6.341***	21.413***
	(2.647)	(0.064)	(0.277)	(1.320)
Remote connection to banks (FT)	4.852***	0.094***	0.878***	2.958***
	(0.375)	(0.007)	(0.035)	(0.145)
Interaction (FT*FD)	-3.352***	-0.067***	-0.633***	-2.062***
	(0.272)	(0.006)	(0.026)	(0.108)

Source: authors' calculations on SHIW HA 10.1. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household income, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. (2) Obs: 103,006; OLS Adjusted R-squared = 0.097; Adjusted R1 = 0.107. (3) Obs: 47,571; OLS Adjusted R-squared = 0.100; Adjusted R1 = 0.120. (4) Obs: 55,435; OLS Adjusted R-squared = 0.097; Adjusted R1 = 0.095. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

Table 7

IV OLS and IV quantile regression parameters for rate of financial returns

(in percentage points)

Characteristics[1]	IV OLS	P10	P50	P90
		A - Total sample (1991–2016) [2]		
Bank branches (FD) (standardised)	5.012***	0.110***	0.779***	2.699***
	(0.212)	(0.003)	(0.018)	(0.082)
Remote connection to banks (FT)	0.589***	0.013***	0.091***	0.281***
	(0.024)	(0.000)	(0.002)	(0.008)
Interaction (FT*FD)	-0.466***	-0.010***	-0.072***	-0.227***
	(0.019)	(0.000)	(0.002)	(0.007)
		B - First period (1991–2002) [3]		
Bank branches (FD) (standardised)	7.740***	0.264***	2.077***	9.325***
	(0.404)	(0.010)	(0.051)	(0.266)
Remote connection to banks (FT)	0.803***	0.030***	0.201***	0.802***
	(0.048)	(0.002)	(0.008)	(0.034)
Interaction (FT*FD)	-0.665***	-0.022***	-0.170***	-0.722***
	(0.032)	(0.001)	(0.004)	(0.018)
		C - Second period (2004–2016) [4]		
Bank branches (FD) (standardised)	1.264***	0.039***	0.249***	0.829***
	(0.144)	(0.002)	(0.009)	(0.071)
Remote connection to banks (FT)	0.241***	0.005***	0.035***	0.120***
	(0.018)	(0.000)	(0.001)	(0.007)
Interaction (FT*FD)	-0.164***	-0.004***	-0.025***	-0.084***
	(0.013)	(0.000)	(0.001)	(0.006)

Source: authors' calculations on SHIW HA 10.1. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and Islands), quintile of household wealth, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. (2) Obs: 103,006; OLS Adjusted R-squared= 0.066; Adjusted R1 = 0.075. (3) Obs: 47,571; OLS Adjusted R-squared = 0.123; Adjusted R1 = 0.091. (4) Obs: 55,435; OLS Adjusted R-squared = 0.103; Adjusted R1 = 0.064. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

Annex A – The SHIW and the measurement of capital returns

The Bank of Italy has conducted the SHIW since 1962 to collect information about the economic situation of Italian households (sources of income and accumulated wealth) together with socio-demographic characteristics of individuals within the household. The survey was conducted on an annual basis up to 1987 with a sample of 4,000 households and every two years with a sample of about 8,000 households since then. The sample is representative of the Italian population. It is drawn in two stages (municipalities and households), with the stratification of the primary sampling units (municipalities) by region and demographic size. In the first stage, municipalities are stratified by region and population size. Within each stratum, the municipalities are selected to include all those with a population of more than 40,000 and those with panel, and randomly selecting smaller towns with probability proportional to the resident population. Within each selected municipality, the households to be interviewed are randomly selected from the civic register. Since 1989 about half of the sample is composed of households participating from at least two waves (panel households).[24]

Although the amount of information collected has increased over the years, the topics collected with continuity concern socio-demographic information about all members of the household (including gender, birth year, province of birth, and education), employment status and income sources, payment instruments and forms of saving, real assets (principal residence and other properties), debts, household expenditure, supplementary pension plans and insurance policies.[25]

In particular, with respect to net worth components, data on real wealth are available since 1977. Financial wealth and liabilities have been collected since 1987 but only since the 1991 survey have the definitions been consistent with subsequent waves. Since then the income and wealth definitions have remained broadly stable.[26]

With respect to capital returns,[27] the SHIW adopts a mixed data collection strategy. For real assets the questionnaire collects information about received rents (for rented houses, premises such as shops, offices, garages or agricultural or non-agricultural land) and of imputed rent (i.e. the rental value of owner-occupied housing) for the household's main residence and other owner-occupied dwellings directly from the households. This choice is based on the assumption that it is reasonable to believe that families are able to offer an adequate assessment about real capital returns because they are better aware of the quality of the housing (such as maintenance status, ancillary services). Rates of return on real properties are generally less volatile than those of financial assets. Moreover, real assets are typically subject to fewer trades during a year.

By contrast, the cognitive effort necessary for respondents to properly provide financial returns is significantly higher. First, the respondent must take into account in the calculation the permanence periods of each asset in his or her portfolio and therefore of

[24] For more details regarding the sample design, see the methodological note in Bank of Italy (2018).
[25] In each survey additional monographic subjects are also collected, such as capital gains, job satisfaction, social capital, inheritance, financial literacy, households expectations
[26] The types of financial assets recorded in the survey questionnaire have only changed slightly over the years, mainly to reflect changes in assets traded in the financial markets. In order to avoid minor differences in aggregate definitions, this paper uses data from the historical archive (SHIW HA 10.1), which provides harmonised data to account for the changes that have regarded the questionnaire over time.
[27] Assets' returns do not take into account capital gains, which are directly observed in the value of the assets held by households at the end of the year.

any trade made during the year. He or she then has to be aware of the returns of each asset throughout the year and therefore also of its variability over time. In this, the respondent has to consider all assets held during the year, even if these were hold only for a short period and are no longer in the household' s portfolio. All this information is difficult to collect from households. Therefore, the SHIW adopts an estimation technique for the value of financial returns. This is based on the value of the stock of assets that the family reported to own at the end of the year and on the assumption that these were held by the family for the whole year and that they had a fixed rate of return.

More in detail, to estimate financial returns, financial wealth (FW_{it}) is divided into categories of assets endowed with similar level of yields and risk.

$$FW_{it} = \sum_{k=1}^{K} A_{itk}$$

where A_{ikt} is the amount hold by household *i* in assets in the *k* category at the end of the year *t*. Hence returns to financial wealth (r_{it}) are estimated using the following formula:

$$\hat{r}_{it} = \sum_{k=1}^{K} A_{itk} r_{tk}$$

where r_{tk} is the average rate of return of assets in the category *k* in the year *t*.

The methodology for estimating financial returns has been constantly refined over time. Until 2012 only two categories where considered simply distinguishing deposits (as described above in point 1) by all the other financial assets. Since 2014 assets have been divided into four broad categories:

1. deposits (bank current and savings accounts, certificates of deposit, repos, post office current, savings account and saving certificates);
2. shares in listed companies;
3. bonds issued by Italian banks;
4. government securities (BOTs, CCTs, BTPs, inflation-indexed BTPs, CTZs, ...) and other securities (bonds issued by Italian firms, fund units, ETFs, shares in unlisted companies, shares in companies limited by shares, equity in partnerships, managed portfolios, foreign securities, loans to cooperatives and other financial assets such as options, futures, royalties, etc.)

In particular, the yield used to estimate returns for government securities and other securities, a weighted average rate is obtained weighting the gross average yield for BOT, BTP, CTZ, and CCT using the corresponding share of each government security hold by Italian households as resulting from the survey. Furthermore, since 2016, thanks also to the greater detail used in the categorisation of securities, the values have been calculated net of taxes, applying, as required by the current tax system, two distinct rates to the yields of government securities (12.5%) and of other securities (26%) to get net returns. To reduce the effect attributable to a potential discontinuity in return values due to the shift from gross to net values, the returns used in this analysis have been calculated all in gross terms.

Annex B – Methodological reconstruction of the financial technology variable

The information about the use of a remote connection by households with banks and financial intermediaries has been collected in the SHIW since 2000. Specifically, the question used is: "*Did you or a member of the household do business with banks or financial intermediaries by telephone or computer in the last calendar year (home banking, online account, ...)? Yes/No*"

To impute the values of the variable for the previous year, we estimate a logistic model of the probability of using a remote connection with banks based on the SHIW 2000–2016 data, using the set of covariates reported in table B.1. According to the model, the probability of using remote banking grows over time. It is higher for households with a current account, with higher levels of financial wealth, for those who own their main residence and those who live in larger cities. Use is also higher in northern and central Italy, for households with children or whose head is male. Finally, use is higher when the head of household has a higher level of education, is aged between 30 and 50 or is self-employed.

We then use the parameter estimated in the model to predict the usage of remote connection backwards, for all the households in the sample for the period 1991–1998. Figure B.1 reports the observed and the predicted values.

Finally, the variable used in the paper to represent innovation in financial technology has been constructed using all the relevant information available: as the diffusion of remote connection to banks in Italy significantly started in 1995 it was set equal to zero before that date, the predicted values have been used from 1995 to 1998 and the observed value from 2000 to 2016.

Figure B.1

Share of household using remote connection with banks

(percentages, observed and predicted values)

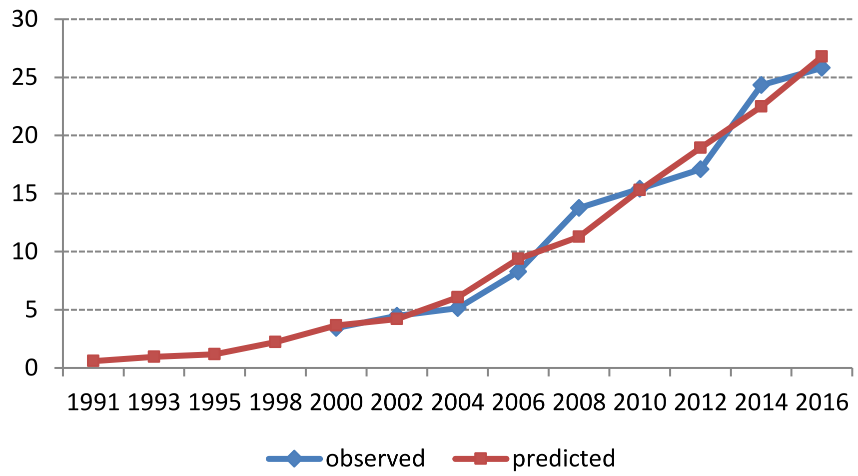


Table B.1

Probability of using remote connection with banks
(logistic model)

Characteristics[1]		Parameter	Standard error	Odds ratio
Intercept		-408.70**	6.236	
Survey year		0.20**	0.003	1.22
Gender	Male	0.34**	0.033	1.40
	Female			
Age	30 and under	0.89**	0.080	2.43
	31–40	1.17**	0.064	3.22
	41–50	1.03**	0.060	2.80
	51–65	0.77**	0.050	2.16
	Over 65			
Born abroad		-0.62**	0.066	0.536
Work status	Employee	0.35**	0.046	1.42
	Self-employed	0.77**	0.051	2.15
	Not employed			
Education	None or Primary school certificate	-2.52**	0.075	0.08
	Secondary school certificate	-1.53**	0.038	0.217
	Upper secondary school diploma	-0.51**	0.034	0.602
	University degree			
Geographical area	North	0.95**	0.036	2.59
	Centre	0.83**	0.041	2.28
	South and Islands			
Town size (inhabitants)	up to 20000	-0.50**	0.051	0.605
	from 20000 to 40000	-0.22**	0.052	0.801
	from 40000 to 500000	-0.22**	0.046	0.806
	over 500000			
Couple in the household		0.25**	0.040	1.284
Children in the household		0.10*	0.045	1.109
Household size		0.04*	0.021	1.045
Quintiles of household (financial) wealth	1º quartile	-1.09**	0.049	0.336
	2º quartile	-0.79**	0.038	0.452
	3º quartile	-0.53**	0.034	0.59
	4º quartile			
Owns household main residence		0.15**	0.034	1.158
Owns a current account		2.44**	0.184	11.48

([1]) Individual characteristics refer to the head of household, i.e. the member with the highest income.

Annex C – Models not corrected for endogeneity

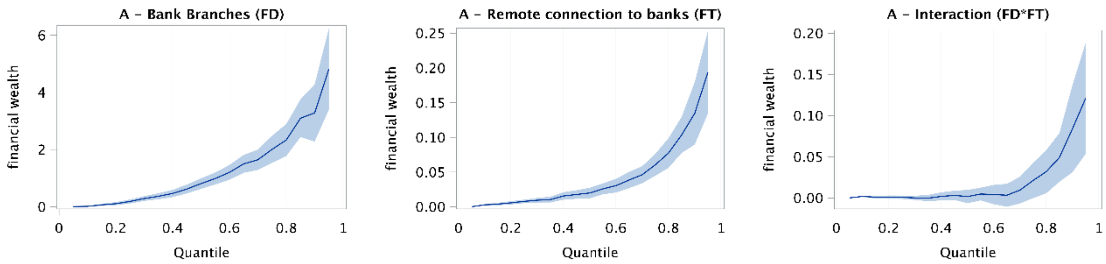
Figure C.1

Estimated parameters by quantile for household financial wealth

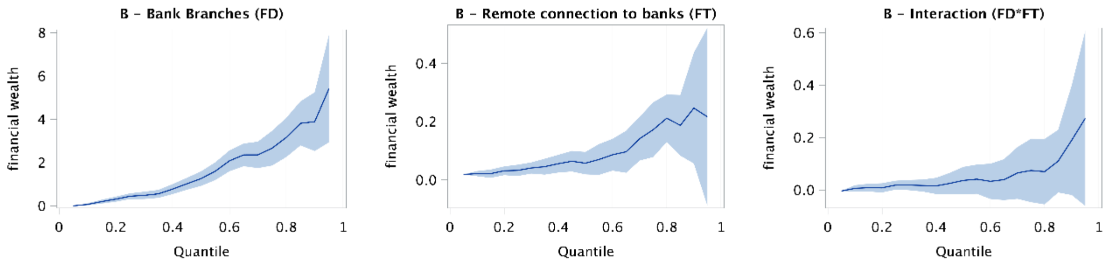
(thousands of 2016 euros)

Bank Branches (FD) (standardised)	*Remote connection to banks (FT)*	*Interaction (FD*FT)*

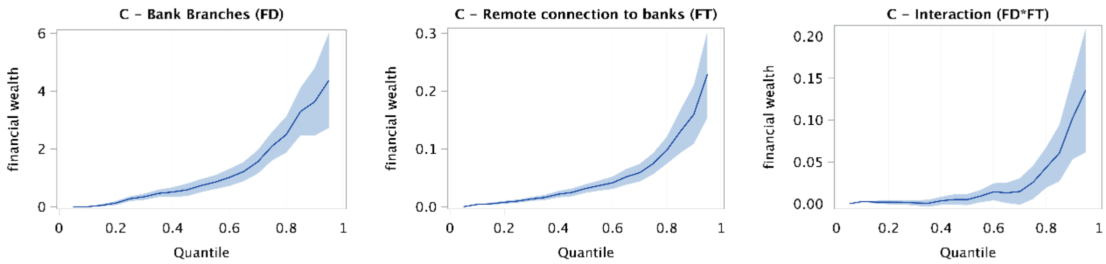
A - Total sample (1991–2016)



B - First period (1991–2002)



C - Second period (2004–2016)



Source: authors' calculations on SHIW HA 10.1. Weighted quantile regressions. Estimate parameters for specific covariates by quantile levels of household financial wealth. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household income and survey year (individual characteristics refer to the head of household, i.e. the member with the highest income). Quantile levels of household financial wealth on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

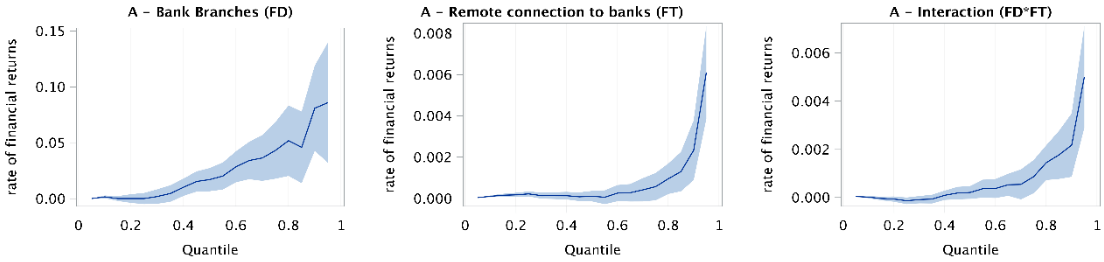
Figure C.2

Estimated parameters by quantile for household rate of financial returns

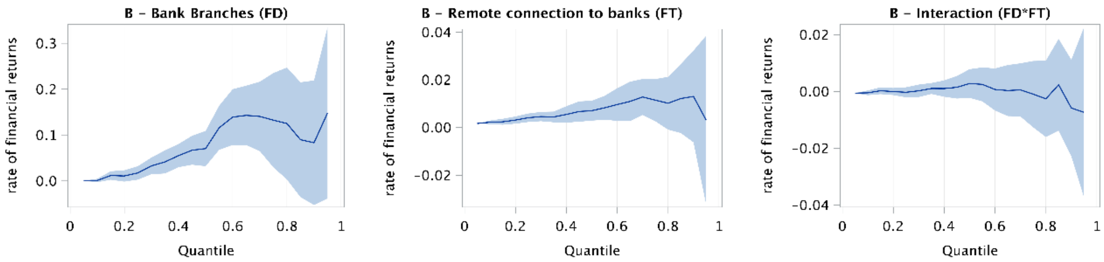
(percentages)

Bank Branches (FD) (standardised) *Remote connection to banks (FT)* *Interaction (FD*FT)*

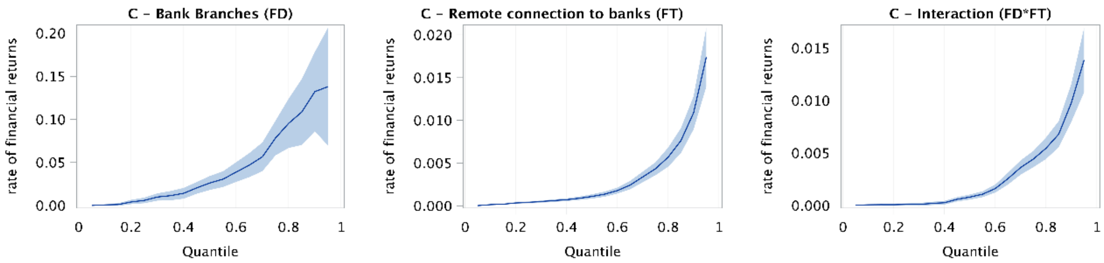
A - Total sample (1991–2016)



B - First period (1991–2002)



C - Second period (2004–2016)



Source: authors' calculations on SHIW HA 10.1. Weighted quantile regressions. Estimate parameters for specific covariates by quantile levels of household rate of financial returns. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household wealth and survey year (individual characteristics refer to the head of household, i.e. the member with the highest income). Quantile levels of household rate of financial returns on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

Table C.1

OLS and quantile regression parameters for household financial wealth

(thousands of 2016 euro)

Characteristics[1]	OLS	P10	P50	P90
	A - Total sample (1991–2016) [2]			
Bank branches (FD) (standardised)	1.250**	0.009	0.807***	3.283***
	(0.510)	(0.006)	(0.094)	(0.511)
Remote connection to banks (FT)	0.139***	0.003***	0.020***	0.135***
	(0.023)	(0.001)	(0.004)	(0.023)
Interaction (FT*FD)	0.028	0.002***	0.002	0.084***
	(0.021)	(0.000)	(0.004)	(0.027)
	B - First period (1991–2002) [3]			
Bank branches (FD) (standardised)	2.382***	0.068***	1.258***	3.889***
	(0.831)	(0.022)	(0.171)	(0.692)
Remote connection to banks (FT)	0.169	0.021***	0.057***	0.246**
	(0.131)	(0.005)	(0.020)	(0.097)
Interaction (FT*FD)	0.114	0.006	0.036	0.189*
	(0.073)	(0.006)	(0.026)	(0.107)
	C - Second period (2004–2016) [4]			
Bank branches (FD) (standardised)	0.823	0.000	0.732***	3.630***
	(0.656)	(0.000)	(0.115)	(0.596)
Remote connection to banks (FT)	0.157***	0.004***	0.031***	0.160***
	(0.020)	(0.000)	(0.004)	(0.026)
Interaction (FT*FD)	0.031	0.003***	0.005	0.102***
	(0.022)	(0.000)	(0.003)	(0.025)

Source: authors' calculations on SHIW HA 10.1. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household income, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. (2) Obs: 103,006; OLS Adjusted R-squared = 0.097; Adjusted R1 = 0.097. (3) Obs: 47,571; OLS Adjusted R-squared = 0.100; Adjusted R1 = 0.104. (4) Obs: 55,435; OLS Adjusted R-squared = 0.097; Adjusted R1 = 0.091. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

Table C.2

OLS and quantile regression parameters for rate of financial returns

(percentage points)

Characteristics[1]	OLS	P10	P50	P90
	A - Total sample (1991–2016) [2]			
Bank branches (FD) (standardised)	-0.143**	0.002**	0.017***	0.081***
	(0.071)	*(0.001)*	*(0.005)*	*(0.020)*
Remote connection to banks (FT)	-0.002	0.000***	0.000	0.002***
	(0.002)	*(0.000)*	*(0.000)*	*(0.001)*
Interaction (FT*FD)	0.003	0.000	0.000	0.002***
	(0.002)	*(0.000)*	*(0.000)*	*(0.001)*
	B - First period (1991–2002) [3]			
Bank branches (FD) (standardised)	0.065	0.001	0.070***	0.083
	(0.148)	*(0.002)*	*(0.02)*	*(0.069)*
Remote connection to banks (FT)	0.019	0.002***	0.007***	0.013
	(0.017)	*(0.000)*	*(0.002)*	*(0.010)*
Interaction (FT*FD)	-0.002	-0.001	0.003	-0.006
	(0.008)	*(0.000)*	*(0.003)*	*(0.009)*
	C - Second period (2004–2016) [4]			
Bank branches (FD) (standardised)	-0.058	0.001**	0.026***	0.132***
	(0.048)	*(0.000)*	*(0.004)*	*(0.024)*
Remote connection to banks (FT)	0.009***	0.000***	0.001***	0.011***
	(0.001)	*(0.000)*	*(0.000)*	*(0.001)*
Interaction (FT*FD)	0.006***	0.000***	0.001***	0.010***
	(0.001)	*(0.000)*	*(0.000)*	*(0.001)*

Source: authors' calculations on SHIW HA 10.1. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, not employed), born abroad, age class (5 classes), geographical area (North, Centre, and South and Islands), quintile of household wealth, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. (2) Obs: 103,006; OLS Adjusted R-squared= 0.066; Adjusted R1 = 0.066. (3) Obs: 47,571; OLS Adjusted R-squared = 0.123; Adjusted R1 = 0.077. (4) Obs: 55,435; OLS Adjusted R-squared = 0.103; Adjusted R1 = 0.061. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

Annex D – Including bank-specific characteristics (2004–2016)

Table D.1

IV estimated parameters by quantile for household financial wealth

(thousands of 2016 euros)

Characteristics[1]	IV OLS	P10	P50	P90
Bank branches (FD) (standardised)	45.79***	1.702***	12.304***	52.583***
	(4.401)	(0.205)	(0.690)	(2.608)
Remote connection to banks (FT)	4.832***	0.124***	1.034***	4.338***
	(0.396)	(0.015)	(0.049)	(0.191)
Interaction (FT*FD)	-2.726***	-0.079***	-0.603***	-2.539***
	(0.230)	(0.009)	(0.030)	(0.123)

Source: authors' calculations on SHIW HA 10.1, 2004–2016. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and Islands), quintile of household income, dummies for survey year and bank-specific characteristics (bank size, capitalisation and liquidity). Individual characteristics refer to the head of household, i.e. the member with the highest income Obs: 55,435; OLS Adjusted R-squared= 0.117; Adjusted R1 = 0.485. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

Table D.2

IV estimated parameters by quantile for household rate of financial returns

(in percentage points)

Characteristics[1]	IV OLS	P10	P50	P90
Bank branches (FD) (standardised)	1.765***	0.053***	0.364***	1.877***
	(0.288)	(0.006)	(0.029)	(0.171)
Remote connection to banks (FT)	0.204***	0.004***	0.032***	0.162***
	(0.017)	(0.000)	(0.002)	(0.011)
Interaction (FT*FD)	-0.103***	-0.003***	-0.018***	-0.092***
	(0.010)	(0.000)	(0.001)	(0.008)

Source: authors' calculations on SHIW HA 10.1, 2004–2016. Notes: (1) Other covariates in the model: gender, university degree, works status (employee, self-employed, not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and Islands), quintile of household wealth, dummies for survey year and bank-specific characteristics (bank size, capitalisation and liquidity). Individual characteristics refer to the head of household, i.e. the member with the highest income. Obs: 55,435; OLS Adjusted R-squared = 0.121; Adjusted R1 = 0.370. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

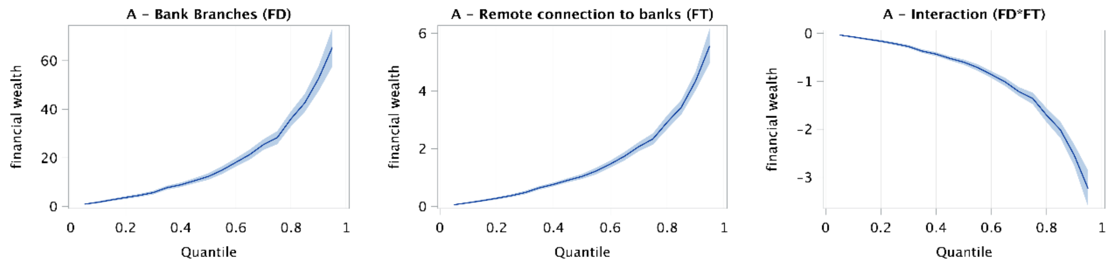
Figure D.1

IV estimated parameters by quantile for household financial wealth

(thousands of 2016 euros)

Bank Branches (FD) (standardised) *Remote connection to banks (FT)* *Interaction (FD*FT)*

(2004–2016)



Source: authors' calculations on SHIW HA 10.1. Weighted quantile regressions. Estimate parameters for specific covariates by quantile levels of household financial wealth. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household income, survey year (individual characteristics refer to the head of household, i.e. the member with the highest income) and bank-specific characteristics (bank size, capitalisation and liquidity. Quantile levels of household financial wealth on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

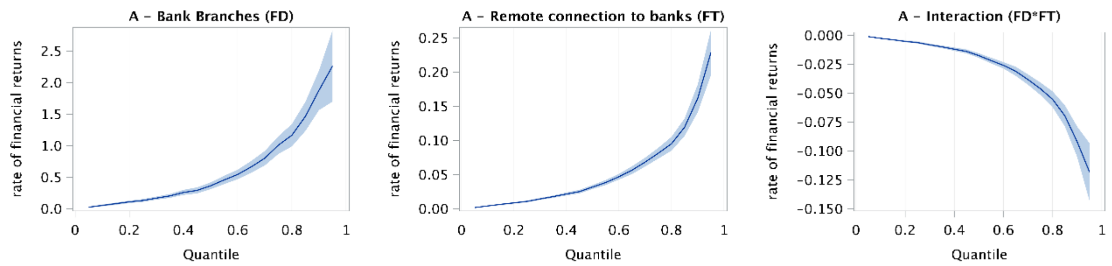
Figure D.2

IV estimated parameters by quantile for household rate of financial returns

(percentages)

Bank Branches (FD) (standardised) *Remote connection to banks (FT)* *Interaction (FD*FT)*

(2004–2016)



Source: authors' calculations on SHIW HA 10.1. Weighted quantile regressions. Estimate parameters for specific covariates by quantile levels of household financial wealth. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (north, centre, and south), quintile of household wealth, survey year (individual characteristics refer to the head of household, i.e. the member with the highest income) and bank-specific characteristics (bank size, capitalisation and liquidity. Quantile levels of household rate of financial returns on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).

Annex E – Analysis for risk-bearing financial assets

Table E.1

IV Quantile and IV OLS regression parameters for household wealth in risk-bearing financial assets[1]

(thousands of 2016 euro)

Characteristics[2]	IV OLS	P10	P50	P90	P95
		A - Total sample (1991–2016) [3]			
Bank branches (FD) (standardised)	13.76***	0.000***	0.000***	0.672***	6.016***
	(1.232)	(0.000)	(0.000)	(0.083)	(0.553)
Remote connection to banks (FT)	2.304***	0.000***	0.000***	0.204***	0.952***
	(0.172)	(0.000)	(0.000)	(0.012)	(0.076)
Interaction (FT*FD)	-1.550***	0.000***	0.000***	-0.058***	-0.528***
	(0.123)	(0.000)	(0.000)	(0.007)	(0.049)
		B - First period (1991–2002) [4]			
Bank branches (FD) (standardised)	14.979***	0.000***	0.000***	4.448***	10.224***
	(1.700)	(0.000)	(0.000)	(0.292)	(1.404)
Remote connection to banks (FT)	2.347***	0.000***	0.000***	2.392***	3.244***
	(0.248)	(0.000)	(0.000)	(0.091)	(0.302)
Interaction (FT*FD)	-1.426***	0.000***	0.000***	-0.310***	-0.784***
	(0.169)	(0.000)	(0.000)	(0.023)	(0.113)
		C - Second period (2004–2016) [5]			
Bank branches (FD) (standardised)	12.215***	0.000***	0.000***	0.045	2.372***
	(1.744)	(0.000)	(0.000)	(0.078)	(0.777)
Remote connection to banks (FT)	2.352***	0.000***	0.000***	0.114***	0.510***
	(0.248)	(0.000)	(0.000)	(0.010)	(0.104)
Interaction (FT*FD)	-1.558***	0.000***	0.000***	-0.010	-0.230***
	(0.177)	(0.000)	(0.000)	(0.007)	(0.075)

Source: authors' calculations on SHIW HA 10.1. Notes: (1) Risk-bearing financial assets include bonds, mutual funds, equity, shares in private limited companies and partnerships, foreign securities, loans to cooperatives and other financial assets. It excludes deposits, certificates of deposit (CDs), repos, postal savings certificates and government securities. (2) Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household income, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. (3) Obs: 103,006; OLS Adjusted R-squared = 0.064; Adjusted R1 = 0.000. (4) Obs: 47,571; OLS Adjusted R-squared = 0.065; Adjusted R1 = 0.000. (5) Obs: 55,435; OLS Adjusted R-squared = 0.0664; Adjusted R1 = 0.000. Standard errors in brackets; *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. Adjusted R1 from Koenker and Machado (1999).

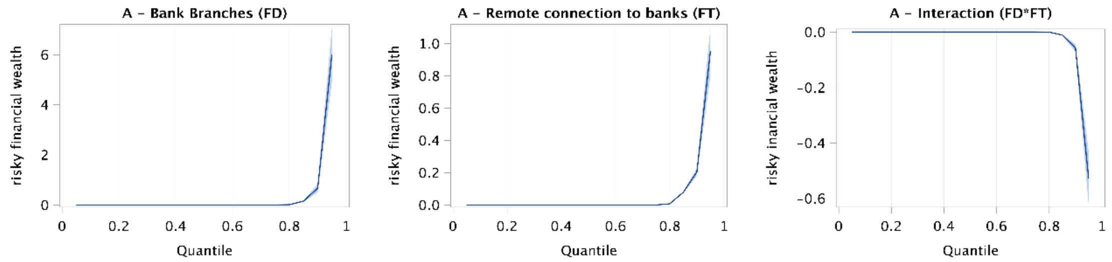
Figure E.1

IV estimated parameters by quantile for wealth in risk-bearing financial assets[1]

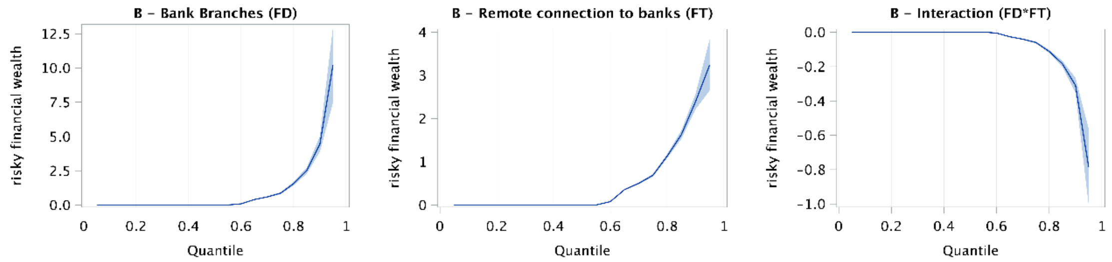
(thousands of 2016 euros)

Bank Branches (FD) (standardised) *Remote connection to banks (FT)* *Interaction (FD*FT)*

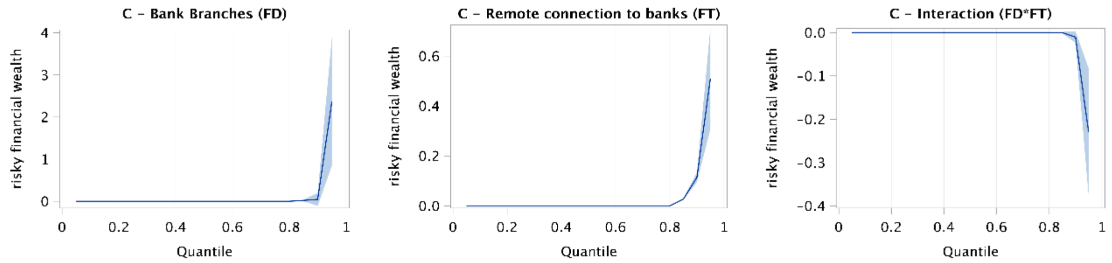
A - Total sample (1991–2016)



B - First period (1991–2002)



C - Second period (2004–2016)



Source: authors' calculations on SHIW HA 10.1. Note: (1) Risk-bearing financial wealth includes bonds, mutual funds, equity, shares in private limited companies and partnerships, foreign securities, loans to cooperatives and other financial assets. It excludes, deposits, certificates of deposit (CDs), repos, postal savings certificates and government securities. Weighted quantile regressions. Weighted quantile regressions. Estimate parameters for specific covariates by quantile levels of households' wealth in risk-bearing financial assets. Other covariates in the model: gender, university degree, works status (employee, self-employed, and not employed), born abroad, age class (5 classes), geographical area (North, Centre, South and islands), quintile of household income, dummies for survey year. Individual characteristics refer to the head of household, i.e. the member with the highest income. Quantile levels of household wealth in risk-bearing financial assets on the horizontal axis. 95% confidence intervals, shown by a blue band, computed by using the Markov chain marginal bootstrap (MCMB) resampling method of He and Hu (2002).