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HOUSEHOLD DEBT AND INCOME INEQUALITY: EVIDENCE FROM ITALIAN SURVEY DATA

by David Loschiavo*

Abstract

Does regional income inequality affect a household's likelihood of being indebted? This question is addressed by using survey data on Italian households. The analysis shows that inequality in the regional income distribution has a negative effect on the probability of being indebted. In addition, richer households living in regions with greater income inequality have a greater likelihood of being indebted than similarly rich households residing in regions with low income inequality (and vice versa for poorer households). The study suggests that supply factors are more important than demand factors in explaining this result. These findings are consistent with the latest survey-based evidence drawn from US data which suggests that banks may use local income inequality and a household's position in the income distribution to make inferences about an applicant's underlying default risk. These results hold after controlling for socio-demographic differences, different types of debt, unobserved household heterogeneity using panel data and a number of robustness checks.

JEL Classification: D14, D63, G01, G21, R10.
Keywords: income inequality, household debt, credit rationing, great recession, regional data.

Contents

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1 Introduction*

In most of OECD countries household debt has reached exceptional levels over the decade before the Great Recession and, in the aftermath of the crisis, the role of household leverage as a potential source of financial instability has become a central question in policy and academic debates.[1] Differences in household debt diffusion are anyway very stark across countries: more limited in Italy than in others (e.g. Spain, Netherlands and USA). Much of the literature on household finance decomposes the sources of cross-country differences into those arising from household characteristics (age, education, income, etc.) and those stemming from the interplay of these characteristics with different economic environments (e.g., Christelis *et al.* (2015); Coletta *et al.* (2014); Jappelli *et al.* (2013); Zinman (2014); Porta *et al.* (1998)). Among the latter factors the role of income inequality has been poorly explored.[2]

Income inequality may affect borrowing from both supply and demand side. From the former, Rajan (2010) argues that the upsurge of credit supply to US lower income households was due to political motivations for supporting their consumption, in response to rising income inequality and stagnant incomes.[3] From the demand side, some studies show that widening economic inequality led households to borrow more to smooth consumption from a more volatile income (Krueger and Perri (2006); Iacoviello (2008)).

The aim of this paper is to explore empirically the relationship between the likelihood of being indebted and local income inequality and to understand the role that supply and demand factors plays in mediating this relationship. I use micro data on Italian households from *Survey on Household Income and Wealth* combined with information on local inequality from *EU-Statistics on Income and Living Conditions* survey. I first explore if the extent of income inequality in a region affects the credit market participation of resident households. Then, following Coibion *et al.* (2014) I compare the probability of debt across income groups located in regions with different degrees of income inequality.[4] As it will be shown in Section 3, this comparison is particularly suitable for the case of Italy where the dispersion of household debt across regions is high and its areas are very heterogeneous in terms of economic structure, households' characteristics and inequality in income distribution. Finally, I test alternative hypotheses about the prevalence of demand or supply factors in shaping the relationship between local inequality and the household probability of

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[1] According to many scholars household indebtedness induced macroeconomic instability in many countries and played an important role in the Great Recession (Mian and Sufi (2015)).

[2] Nevertheless, in the recent years, a growing interest has been devoted to the impact of income inequality on potential growth and its role in causing the crisis and the weak recovery (e.g., Fitoussi and Saraceno (2010); Piketty (2014); Summers (2014); Ostry *et al.* (2014); Atkinson and Morelli (2015)).

[3] From the supply-side, see also Kumhof *et al.* (2013) suggesting that permanent positive shocks to the income share of high-income households led to increased supply of loanable funds to poor and middle-income households, allowing the latter to sustain higher consumption levels.

[4] Despite this, there remain some important differences with my paper. See Section 2.

holding a debt, using information on loan demand and credit rationing.

To the best of my knowledge, this is the first paper that study the impact of local inequality on debt outcomes for a representative sample of Italian households, whereas the evidence available is scant and focused on countries such USA and Netherlands where the incidence of households with debts is relatively high.[5] The Italian case is interesting because of the limited diffusion of debt, the high heterogeneity in regional income inequality, and a distribution of debt highly skewed towards high-income households. Furthermore, survey data used allow to exploit panel data and to observe the effect of local inequality on loan demand and credit rationing.

The analysis provides evidence that income inequality affects negatively households' credit market participation and that the more unequal is a region the more the indebted households are concentrated among the richer ones. The findings are found persistent after controlling for socio-demographic differences and according to a number of robustness checks. Moreover, local inequality does not seem to affect the likelihood to apply for a loan, but decreases the probability of loan application refusal for top income households (vice versa for the poorer ones). Such results are consistent with Coibion *et al.* (2014) model in which "banks use an applicant's position in the local income distribution, along with the dispersion of that distribution, to make inferences about default risk". Although in line with the predictions of their model, it is worth stressing that my results empirically depart from theirs, mainly due to the differences between Italian and US household debt markets.[6] In addition to this, as it will be highlighted in the next section, this paper contributes further to the comprehension of the almost neglected role of income inequality on household debt diffusion.

The remainder of the paper is organized as follows: Section 2 reviews the related literature and highlights the contributions of this analysis; Section 3 describes the dataset and documents some stylised facts which motivates this work, Section 4 discusses possible channels through which income inequality might influence borrowing and lending behaviours and lays out the empirical strategy, Section 5 presents the main results, Section 6 extends the analysis to different types of debt and compares pre-crisis and crisis periods; Section 7 presents the robustness checks, Section 8 concludes. Appendix A contains a comparison of descriptive statistics from the two surveys exploited in the paper.

[5]There are only two other papers which provide evidence on the relationship between local inequality and household borrowing patterns at micro-data level. Georgarakos *et al.* (2014) use Dutch household survey data to assess the effects of social interactions on the decisions to take on different types of debt. They find that a higher average income in the social circle, as perceived by a household, increases the probability that this household will have outstanding and sizeable loans. On the other side, using US household level data, the work of Coibion *et al.* (2014) finds evidence of a systematic relationship between local inequality and differential borrowing patterns across richer and poorer households in the US. Furthermore, they present a model that provides one potential supply-side explanation for their results (see Section 2).

[6]See Section 5.3 for more details.

2 Related Literature

This paper relates to different strands of literature. First, it contributes to the literature studying the determinants of households' participation to the debt market, and more specifically to the literature on the importance of relative income for household consumption, debt and portfolio decisions. Households with incomes below average in their social circle tend to consume a larger share of their income to keep up with peers.[7] The problem of "keeping up with the Joneses" has been proposed as explanation for U.S. households overspending and excess of labour supply Stiglitz (2012). Georgarakos *et al.* (2014) provided evidence that the signalling motive and concerns about social influence might feature in borrowing decisions.[8] The empirical setting adopted in this work allows to test "keeping up with the Joneses" influence on loan demand by confrontation of potential differential borrowing patterns across richer and poorer households located in high or low inequality regions.

The paper also relates to the literature on adverse selection in imperfect credit markets and its effects on banks' lending policies. Starting with the classic work of Stiglitz and Weiss (1981) a large body of research shows how imperfect information can lead to credit rationing (e.g., Bester (1985); Besanko and Thakor (1987)). Since creditworthiness is private information, banks may use local income inequality, together with applicant's position in the local income distribution, to screen borrowers as in standard models of financial contracting under adverse selection. Coibion *et al.* (2014) present a model that provides one potential supply-side explanation for why differential borrowing behaviours could be related to regional inequality. Each region is composed of two types of households, such that "high-type" households have higher income on average than "low-type" households, and are also less likely to default on debt. Banks in each region lend to these households, but do not observe households' types - only their income and another signal (not observed by the econometrician) correlated with the underlying type. The key mechanism in the model is that as local income inequality rises, banks treat an applicant's income as an increasingly precise signal about their type, and therefore will make credit more readily accessible (or cheaper) to high-income households.

Directly inspired from the model of Coibion *et al.* (2014), this paper aims at taking further steps in the comprehension of the almost neglected role of income inequality for borrowing patterns and lending decisions. To this end, the analysis focus on Italian economy where there are substantial differences in household debt diffusion and income inequality across regions. Differently from Coibion *et al.* (2014),[9] the present analysis is on the diffusion of debt and on the influence that

[7]The idea that concerns about social status may shape consumption decisions can be traced back to the works of Veblen (1899) and Duesenberry (1949).

[8]Other contributions point to the relevance of the "keeping up with the Joneses" phenomena: Bertrand and Morse (2013) have documented the importance of trickle-down consumerism, showing that not only does spending increase if one lives in a community with higher income inequality, but so do bankruptcy and self-reported financial distress; Frank *et al.* (2014) have put forward a similar hypothesis, called "expenditure cascades". They provide empirical evidence that increased income inequality is associated with overspending, reflected in, for instance, higher bankruptcy rates. Using US survey data, Bricker *et al.* (2014) find that a household's income rank is positively associated with its expenditures on high status cars, its level of indebtedness, as well as the riskiness of its portfolio.

[9]In their analysis they are interested in explaining the exceptional rise in debt accumulation in

inequality may exert on the extension of household debt market in Italy. This work takes advantage of the richness of data used that allow to observe separately loan demand and credit rationing. This helps to test alternative theoretical predictions on the role of income inequality on household debt market participation, shedding more light on their relative importance. Moreover, by exploiting the longitudinal feature of SHIW survey, this paper may also take into account unobserved household heterogeneity.[10] Finally, the work suggests a potential explanation of the reason why information contained in the income signal get stronger when inequality is higher; highlighting, in particular, the role played by the persistence of income inequality for credit rationing (see Section 4).

3 Data, stylized facts and motivation

3.1 Data sources

The data used in the analysis are obtained from different sources. The main one is the *Banca d'Italia's Survey on Household Income and Wealth* (SHIW), which has been carried out biennially since 1987.[11] The sample used for this analysis consists of the five waves 2004-2012, covering approximately 40,000 households (of which nearly 10,000 panel households).

Since regional variations in income inequality are higher than time variations at the national level, to identify any potential effect of inequality on household behaviour the existing empirical literature focus on the level of *local* inequality. The central idea is that the social interactions and relative positioning among neighbours shape the relationship between borrowing patterns and inequality, making geographic proximity a key dimension for the definition of both the relevant reference group in the case of demand-driven patterns and for the relevance of the signalling channel in the supply-side case.[12] However, narrowing down to a very fine level of spatial aggregation might raise endogenous sorting problems that can bias results. On the other side, households might have stronger incentives to signal their relative income rank at more local levels. Bearing this potential trade-off in mind, the focus of this work will be at the level of Italian regions (NUTS 2) that in this analysis it is deemed a level of spatial aggregation in which these signalling effects may still persist whereas the risk of unobserved factors that determine both

the US patterns across different segments of the population over the course of the 2000s.

[10] Furthermore, the dataset used include information on households' income so that, unlike the work of Coibion *et al.* (2014), it is not needed to apply any kind of income imputation.

[11] Over the years, the scope of the survey has grown and now includes information on income, wealth composition, loans, and social, demographic and economic characteristics of approximately 8,000 households (24,000 individuals), distributed over about 350 Italian municipalities. The sampling is in two stages: first municipalities are chosen from different strata from throughout Italy and then households are randomly chosen from registry office records within each chosen municipality. Up to 1987 the survey was conducted with time-independent samples (cross-sections) of households, since 1989 part of the sample has comprised households interviewed in previous surveys (panel households). Comprehensive descriptions of the survey are given by Brandolini and Cannari (1994) and Guiso and Jappelli (2002).

[12] The existing literature ranges from as aggregated a geographic level as the state to as fine a level as the Metropolitan Statistical Area. Other works, thanks to a rare availability of data, narrow the context where inequality impacts on household debt at the finer level of zip codes.

household selection into an area and its borrowing behaviour is strongly reduced.[13]

However, the SHIW survey sample is not designed to be *representative* at the *regional* level. To overcome this limitation, I construct regional income inequality measures from the Italian leg of the Eurostat's EU-SILC survey (*EU-Statistics on Income and Living Conditions*), which is designed to be representative at regional level, counting approximately 19,000 households (41,000 individuals).[14]

Given that EU-SILC data are available since 2003, I pool data from the 2004 to 2012 SHIW waves, a time span which allows comparisons between the periods before and during the crisis.

I use households' residence and merge social and economic data with information drawn from other sources. Data on credit quality are from the *Italian Credit Register* (henceforth, CR) owned by Banca d'Italia. Data on house prices are obtained from *Observatory of the real estate market* managed by Agenzia delle Entrate (AdE - the Italian Revenue Agency).

Sample restrictions I apply various selections to the dataset. First, only households with positive income are considered. Second, to minimize potential age related selection effects, I restrict the sample to households whose head is older than 20 or younger than 70. Finally, in order to avoid outliers influencing the estimation's results, I also exclude the observations in the 1st and the 99th percentile of the distribution of disposable income. After having applied the mentioned selections, the sample used in the baseline estimations consists of 29,282 observations (17,038 households) in the cross-section dataset and of 7,762 observations (1,816 households) in the panel dataset.

3.2 Motivating facts

Table 1 provides summary statistics on debt holders by SHIW survey year. Data show that the percentage of households with debt increases until 2008 and decreases after the eruption of the crisis. In each wave the frequency of debt monotonically increases with households' income quartiles and is higher among middle age, more educated and larger families.

Figure 2 and 3 show how the percentage of households indebted in Italy is the lowest among Euro area countries, albeit there are sizable differences across Italian regions: credit market participation is higher in Central and in some Northern regions (Lombardy and Veneto), whilst far below the average in Southern regions particularly.

Figure 4 plots Gini coefficients of equivalised[15] income across regions. Inequality is higher in the Southern regions, as well as in some regions of Centre and Northwest

[13]Moreover, the analysis is focussed on local income inequality for other two reasons: first, this is likely to be the most relevant metric when households compare themselves to others; second, it avoids measurement issues associated with comparing incomes across very different regions.

[14]In Appendix A, it is shown a general good fit between SHIW and EU-SILC estimates of equivalised household incomes in terms of quartile distribution, inequality indices and their time trends.

[15]In the following analysis I will always refer to equivalised household (monetary disposable) income which is normally considered the most appropriate indicator of the standard of living of a family. Equivalised household income is total household income adjusted by the application of an equivalence scale to facilitate comparison of income levels between households of differing size

Italy (Lazio and Liguria), lower in Northeast regions. Overall, regional differences in income inequality are substantial: in 2012 the average Gini coefficient was of 0.30 with a standard deviation of (0.03) and, therefore, a coefficient of variation of 9.2%.[16] These stylised facts support the first research question of this work: is there a link between the degree of inequality in the regional income distribution and the frequency of households with debt?

A *prima facie* evidence is provided by Figure 5 plotting the share of households with debt against the Gini coefficient per annum for all Italian regions. The negative correlation between the two measures is quite apparent, suggesting that the incidence of household with debt is lower in regions with a higher degree of income inequality and vice versa. This, in turn, leads to the following analysis of how could differences in inequality relate to household debt diffusion.

4 Effects of the local income inequality on households' credit market participation

4.1 Possible Channels

Income inequality may influence households' debt from both demand and supply side. From the former, households below the top percentile in the income distribution might aspire to imitate consumption patterns of richer ones. Thus, a potential effect of income inequality is that households tend to take on debts to keep up with peers. I call the hypothesis that higher inequality implies an increase in leveraged low-income households the "keeping up with the Joneses" influence on loan demand.[17]

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and composition, reflecting the requirement of a larger household to have a higher level of income to achieve the same standard of living as a smaller household. To derive equivalised household income I use the modified OECD scale of equivalence, which assigns a coefficient of 1 to the head of household, 0.5 to other household members aged 14 or more, and 0.3 to those younger than 14. For each household the number of "equivalent adults" is calculated by summing the coefficients assigned to the various members. Household income is then divided by that coefficient and allocated to each household member. For more details see the (Canberra Group, 2011, pp. 68-72). Finally, by monetary disposable income it is meant disposable household income net of imputed rents and gross of negative interests.

[16]Income, consumption and wealth inequalities in Italy have been thoroughly documented by Jappelli and Pistaferri (2010). They find that, between 1980 and 2006, income inequality was higher and has grown faster than consumption inequality. More recently, Acciari and Mocetti (2013) using Italian administrative fiscal data show that there is strong heterogeneity of inequality in income distribution among Italian regions, with Southern ones on average more unequal than Northern regions, and among cities of different size, with biggest metropolitan areas more unequal than smaller cities.

[17]There are a number of similar, albeit different, channels that may influence loan demand. For example, the so-called "getting ahead of the Joneses" effect may occur when wealthier households care more about their social position than poorer ones, and their marginal utility rises when their relative wealth position advances. Near-to-top-rank households might use consumption of status good to signal information about their wealth rank to others in their social or reference group. The desire to signal their status as richer than actually it is may push some households to access credit to buy luxury goods. Another potential channel is when increased inequality have a welfare-enhancing "anticipatory feelings" effect which Hirschman and Rothschild (1973) named "Tunnel Effect". The idea is that individuals observing other people's faster income growth interpret this movement as a sign that their own future income is likely to move in the same direction as that of one's social circle (Senik (2008)). Those at the bottom of the income ladder may therefore be

From the supply-side, according to the channel highlighted in Coibion *et al.* (2014) which I would refer to as "signalling channel" influence on loan supply, top-income households located in highly unequal regions are deemed safer borrowers than the corresponding ones residing in low-inequality regions. The rationale of their model being that banks cannot observe borrower's ability to meet debt obligations so that they take observed income, together with its rank in the local income distribution, as a signal: higher income rank means higher ability to pay but the signal is stronger when inequality is higher. So banks give more importance to it and enable relatively more access to credit to high-income households either by charging lower interest rates or by denying loans less often.[18] A possible explanation for why increased inequality enhances the signal embedded in the relative income is that local inequality is negatively correlated with the income mobility, therefore banks are likely to restrict access to credit to high-income applicants less often than they would do if inequality were lower.

Indeed, during the underwriting process banks are interested in a borrower's willingness and capacity to repay obligations. The borrower's willingness to repay is assessed largely by subjective factors, such as the applicant's past credit history, and instituitional ones (e.g. the strength of lenders' legal protection and the average time to resolve insolvencies for the judicial system). Capacity is determined by the borrower's ability to generate cash flow to service the interest and principal on the loan in the future. However, since creditworthiness is private information, banks observe neither the ability nor the willingness. It follows that they need to infer the probability of default of prospective borrowers on the basis of information available at the present and that best predict his/her future ability to meet obligations. In their screening technology banks usually exploit both hard and soft information: using two surveys carried out in 2006 and in 2009 by the Bank of Italy, Del Prete *et al.* (2013) show that, despite the wide usage of rating and scoring methodologies, Italian banks adopted these devices in a flexible way, giving importance to both hard and soft types of information in their lending decision.[19]

More in general, current income is obviously the main factor that demonstrates capacity to repay debt in the present. Nevertheless, to mitigate the probability of default in the future banks are also interested in the stability over time of this income. Thus, additional information available at the moment of the lending decision need to be taken into consideration, along with the level of current income, as a basis to develop reasonable expectations about the future borrower's ability to meet its obligations.[20] Examples are the job status of the borrowers (employee versus self-employed) or the type of job contract (permanent versus temporary contract). Yet,

encouraged to enter the debt market as they decide to anticipate future expected income through credit to smooth consumption. Finally, negative income shocks affecting more poors raises their probability of seeking credit to smooth consumption and therefore of being credit coinstrained (Denk and Cazenave-Lacroutz (2015)).

[18]See Section 2 for more details.

[19]Moreover, the relevance of ratings in deciding whether to grant a loan declined during the period between the two surveys: in 2009 the percentage of banks considering rating and scoring methodologies not important for their decision to grant a household loan ranged from 25 percent of the large and medium size banks up to nearly two thirds for smaller banks.

[20]There is wide evidence that banks' credit supply decisions are led by uncertainty about future income more than households' current income level (Cannari and Ferri (1997); Magri (2007); Michelangeli and Sette (2016)).

an emerging body of evidence has highlighted that the higher the income inequality the stronger is the persistence of income position over time (Kopczuk *et al.* (2010); Stiglitz (2012)): i.e. those at the bottom of the income distribution have a good chance of remaining there, and as do those at the top.[21] In other terms, the rank in the local income distribution of a household at time t is a better predictor of its rank at time $t+x$ if it lives in highly unequal region rather than if it is situated in a low inequality one. Preliminary evidence suggests that the same also holds true for Italian households.[22] It follows that income inequality strengthens the signal embedded in the current income, enhancing the screening capability of lenders. This is relevant for banks' screening policy and lending decisions in a context of financial contracting under adverse selection.[23]

All in all, local income inequality may be a useful signal for screening borrowers in the sense that current income position is a stronger signal of creditworthiness when inequality is higher.

4.2 Empirical strategy

The aim of this analysis is to examine the effect of local income inequality on households' credit market participation. To this end, I first estimate the probability that a household has a loan, as a function of its position in the local income distribution, conditional on local income inequality. Following Georgarakos *et al.* (2014) and Coibion *et al.* (2014), in the benchmark specification equations of this type are

[21] Moreover, as inequality increases is more likely that the current household's position in the income distribution will persist (Stiglitz (2012); Galor and Zeira (1993); Piketty (1997)). In other terms, the mechanism (or the set of mechanisms) causing the persistence of inequality seems to be more "effective" the higher is the current level of inequality (Corak (2013)); the reasons lying in greater opportunities for top-income households and in the concentration of power so that some groups are in a position to structure policies in their own favour (Dabla-Norris *et al.* (2015); Putnam (2000); Bourguignon and Dessus (2009); Acemoglu *et al.* (2005); Claessens and Perotti (2007)) or in the capacity of getting higher returns on wealth if this is more concentrated (Fagereng *et al.* (2016); Saez and Zucman (2016)).

[22] In fact, SHIW data confirm this prediction. Focussing only on the panel households in years 2004 and 2012 (the beginning and end of the analysis timespan), a number of measures that capture the correlation in household's income rank between the two years indicate that there is a stronger persistence of the households' position (Income Decile) in the local income distribution when inequality is high. For instance, the Pearson correlation coefficient between the initial (at year 2004) and the final (at year 2012) households' rank in the income distribution is greater for households living in high inequality regions than for ones located in low inequality areas.

[23] Thus, if two borrowers have the same level of current income and belong to the same income position in the local income distribution but they are living in areas with a different degree of income inequality, then the income of the borrower residing in the high-inequality region is, *coeteris paribus*, likely more persistent over time than the one of the corresponding borrower living in low-inequality area. In this way, the income of the former is a stronger signal of its future income because its income position is more persistent when income inequality is higher. It should be stressed that the relevant dimension of persistence is a positional one: i.e. separately from any changes in the shapes of the marginal distributions that may occur. In fact, the way in which shocks affecting the whole economy impact individual income movement over time are not easily predictable. For example, equiproportionate income growth does not alter each person's position relative to the position of others. On the other hand, the intensity of an income shock to the economy may not be the same along the income distribution (arguably higher for poorer and lower for richer in the case of a negative shocks (Denk and Cazenave-Lacroutz (2015)).

estimated:

$$\begin{aligned} Debt_{irt} = &\alpha IncDecile_{irt} + \beta Gini_{rt} + \gamma IncDecile_{irt} * Gini_{rt} + \\ &+ \delta \mathbf{X}_{irt} + \phi \mathbf{Z}_{rt-1} + d_t + m_a + \epsilon_{irt} \end{aligned} \tag{1}$$

where $Debt_{irt}$ denotes a binary ownership indicator of debt of household i that resides in region r and where $2004 \leq t \leq 2012$; $IncDecile_{irt}$ is the household's equivalised income decile in the local income distribution which express its relative rank; and $Gini_{rt}$ is the region's r Gini coefficient,[24] the adopted inequality measure. $\mathbf{X}_{irt}$ and $\mathbf{Z}_{rt-1}$ represent, respectively, vectors of household-specific and location-specific controls. Household own characteristics include the level of equivalised income, the age, age squared, educational attainment and marital status of the head of the household, household size, whether household dissaved. I also use dummy variables for households living in municipalities with fewer than 20,000 inhabitants and for self-employed workers. Controls at regional level include the ratio of new bad debts, the growth rate of loans to household sector and the growth rate of housing prices. In addition, I control for time d_t and macro-area fixed effects m_a.[25] Furthermore, in some specifications also regional or province fixed effects are included. Table 2 shows correlation coefficients among the exogenous variables. One may be worried that household-level contemporaneous controls are a potential source of bias. In the robustness analysis presented in Section 7 it is shown that the results are unaffected when I consider a specification in which the measure of local income inequality as well as all the household-specific controls are fixed at the values of the beginning period (2004). ϵ_{irt} denotes the error term. In presence of the interaction effect $IncDecile_{irt} * Gini_{rt}$, α (β) would represent the effect of Income Decile (Gini) on the probability of debt when Gini coefficient (Income Decile) is zero. Both cases do not exist in practice and, consequently, they are not particularly interesting. To enhance the interpretability of coefficients I centre the two control variables first (by subtracting the relevant median value from each case), and then compute the interaction term and estimate the model. After having centred the two variables, α (β) represents the effect of Income Decile (Gini) on the probability of debt when Gini coefficient (Income Decile) is equal to its median value.[26]

By estimating equation (1) I test different hypotheses of how borrowing and inequality interact. If both β and $\gamma = 0$, then local inequality is irrelevant for household borrowing decisions. Differently, if either β or γ significantly differ from zero then local inequality plays a role in determining the probability of being indebted. In the latter case, the observed equilibrium relationship between the local

[24]The Gini concentration index measures the degree of inequality in the distribution of a given variable such as income or wealth; expressed in percentages, it is equal to zero if all households have the same amount of the variable and to one in the case of total inequality, *i.e.* where a single household possesses the total amount of the variable. I derive the Gini index from monetary disposable household incomes so that I am dealing with net (after taxes and transfers) inequality rather than market (before taxes and transfers) inequality; the former being the more appropriate definition of inequality for the phenomena under scrutiny in this paper.

[25]Standard errors of all pooled estimates are clustered at household level in order to deal with the panel component of the data and correct for serial correlation.

[26]Motivations for employing variable centring include also reducing multicollinearity between "conditional main effects" and interaction effect. See Jaccard and Turrisi (1990), (Aiken and West, 1991, pp. 35-36), (Kam and Franzese, 2003, p. 3), (Brambor *et al.*, 2006, p. 71).

inequality and debt market participation may be driven by a combination of demand and supply factors.

The adopted specification allows to investigate this further since the sign of the interaction coefficient (γ) helps to determine whether local inequality affects households' borrowing patterns differently across income groups and to shed more light on the prevailing channel of effects described in Section 4.1. This, in turn, will help to assess if credit demand or supply factors are more important in practice.

Of course, the two scenarios are not mutually exclusive, since, actually, it is possible that both relative demand and supply factors are at work at the same time. In fact, by only observing a household with zero debt it is not possible to distinguish if this is either the exclusive outcome of the demand process or it reflects rejected loan applications. In other terms, there are various ways for a household to have zero observed debt holding: there are those who are not interested in debt market participation; those that want a positive amount of debt and actually do not apply for a loan because they are discouraged either directly from the loan officer or, indirectly, by the prospect of possible rejection; and those that apply and may be rejected by the lender.

To better evaluate the role that credit demand and supply factors play in determining the observed outcome, I thereby take a futher step and follow the empirical strategy adopted in Magri (2007) by exploiting a different group of SHIW questions that allows to single out *i*) those households that asked for a loan in the year regardless of whether they got it or not from those that did not apply for a loan, from *ii*) those households whose applications have been rejected from those that have been accepted. In this way it is possible to separately observe the role of local inequality, interacted with household position in the local income distribution, among determinants of loan demand and the variables affecting the bank's evaluation process.

Loan demand In order to evaluate separately those factors acting on the *demand-side*, I estimate the probability for a household of demanding a loan, using as explanatory variables only a subset of the ones in the baseline specification (1) that literature has suggested they may affect household borrowing decisions. I exclude thereby both the ratio of new bad debts and the growth rate of loans to household sector from vectors of location-specific controls $\mathbf{Z}_{rt}$ and then run the following regression:

$$\begin{aligned} Demand_{irt} =& \alpha IncDecile_{irt} + \beta Gini_{rt} + \gamma IncDecile_{irt} * Gini_{rt} + \\ & + \theta \mathbf{X}_{irt} + \tau \mathbf{Z}^{D}_{rt-1} + d_t + m_a + \epsilon_{irt} \end{aligned} \tag{2}$$

where $Demand_{irt}$ denotes a binary variable indicating whether or not household i that resides in region r asked for a loan in the year t. $\mathbf{Z}^{D}_{rt-1}$ is the vector of location-specific controls relevant for household loan demand that now includes only the regional growth rate of housing prices; while the other controls are unchanged with respect to (1). In addition, I control for time d_t and area fixed effects m_a.

Equation (2) allows to test if local inequality influence household loan demand with the interaction effect being the key variable to determine through which of the channels described this possible influence may be exerted.

Credit rationing In order to evaluate separately the *supply side* of the market, I also estimate the probability that a household application is rejected, conditional on having applied for a loan:

$$\begin{aligned} Raz_{irt} =&\alpha IncDecile_{irt} + \beta Gini_{rt} + \gamma IncDecile_{irt} * Gini_{rt} + \\ &+ \mu \mathbf{X}^S_{irt} + \rho \mathbf{Z}^S_{rt-1} + d_t + m_a + \epsilon_{irt} \end{aligned} \tag{3}$$

where Raz_{irt} denotes a binary variable indicating whether or not household i that resides in region r has been credit rationed in the year t, provided that it applied for a loan.[27] I use as controls only the subset of exogenous variables included in specification (1) that in literature have been identified as relevant for bank decision to grant a loan.[28] Thus, $\mathbf{X}^S_{irt}$ and $\mathbf{Z}^S_{rt-1}$ are, respectively, the vectors of household-specific and of location-specific controls that affect lender decisions to rationing; while other controls remain unchanged with respect to specification (1). In addition, I control for time d_t and area fixed effects m_a. Equation (3) allows to assess the relative importance of supply factors in determining the outcome observed in (1). In this specification, the probability of rationing is observable only for households that have demanded a loan. To control for the possible selectivity implied in excluding those not asking for a loan, I also estimate a standard Heckprobit approach, thus directly assessing the relevance of selection. Following Magri (2007), the chosen exclusion restriction necessary to identify the model is the dummy variable for household living in a small municipality, with fewer than 20,000 inhabitants. The hypothesis is that *Small City* is an important factor in modelling the entry costs in the debt market and thus for the decision whether or not to borrow, but that this is not an important factor in the lender's decision to grant a loan.

In the following Section, I first report the results of the econometric estimation of the probability of holding a debt (1) and then I turn to the results for the loan demand (2) and credit rationing equation (3) respectively.

5 The empirical results

5.1 Probability of holding a debt

Table 3 presents the main estimates for the effect of local inequality on the probability of being indebted. I first discuss the effect of local inequality on the probability of holding any type of debt and then turn to the effects of other independent variables.

[27] The equation mirrors a stringent definition of being credit constrained in the sense that one can only be constrained if one actually applies for credit and is rejected. Other laxer definitions adopted in literature include as constrained (i) those who did not actually apply but who wished to have credit nevertheless and did not receive it; (ii) those who report that they have been rejected or unable to gain all of the amount they applied for or who report that they were discouraged from applying. Because of the SHIW questionnaire design, it not possible to distinguish households belonging to the last two categories.

[28] $\mathbf{X}^S_{irt}$ include the equivalised income, age, age squared, educational attainment and marital status of the head of the household, household size, a dummy variables for self-employed workers. Controls at regional level $\mathbf{Z}^S_{rt}$ include the ratio of new bad debts and the growth rate of housing prices.

Column 1 displays results from a simple LPM regression (Linear Probability Model) run on the pooled dataset (years 2004-2012). The LPM estimation has the advantage of making the interpretation of the coefficients easier, in particular in the case of interaction term.[29] The coefficients from the LPM regression are presented with robust standard errors clustered at the household level in order to deal with the panel component of the data and correct for serial correlation.[30] As expected from descriptive statistics reported in Section 3.2, the coefficient associated to $IncDecile_{irt}$ is positive so that households belonging to top-income groups have a significantly higher probability to be indebted than poorer ones. Furthermore, the relevance of regional income inequality for household borrowing and its negative correlation with the frequency of debt, as anticipated in Figure 2, are confirmed by the significantly negative coefficient of $Gini_{irt}$: the probability of being indebted is higher the less unequal is the region where the household resides. Finally, the coefficient of the interaction between local inequality and household income decile is positive and significant, which suggests that the negative effect of $Gini_{irt}$ on the probability of being indebted is weaker (stronger) when household rank is high (low). The result points to the *supply-side* hypothesis, presented in Section 4.1, according to which poorer household loan demands are rejected by banks more frequently when local income inequality is higher.

Figure (1) presents these results graphically. Panel (a) of Figure (1) plots the relationship between regional Gini coefficient and the estimated likelihood of debt for each household income decile. The graph shows that, as income rank increases, the negative effect of local inequality on probability of debt gets smaller and smaller till reversing for the top income deciles. Panel (b) of Figure (1) plots the relationship between income decile and likelihood of debt for the highest and the lowest level of local inequality. The graph shows that increased inequality allows high-income (low-income) households to borrow more (less) frequently. In fact, households with rank to the right of the crossing are more likely indebted on average as inequality increases; whilst households to the left of the crossing are less likely indebted as inequality increases.

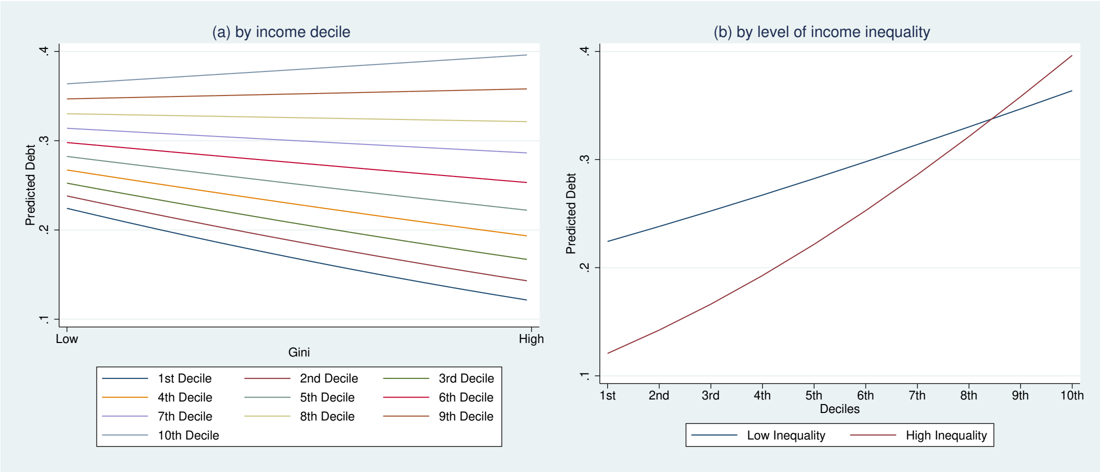
To take into account the well-known limitations of the linear probability model, Column 2 of Table 3 reports the estimated marginal effects from a pooled probit model which shows that the results are substantially equivalent both in terms of the statistical significance, signs and size of the coefficients, as well as in their economic implications.

SHIW data has a household panel component which I exploit to control for unobserved heterogeneity via individual household effects and to track changes in

[29]Interaction effects interpretation is more complicated in nonlinear models because, like the marginal effect of a single variable, the magnitude of the coefficient depends on all the covariates in the model. In addition, it can have different signs for different observations, making simple summary measures of the interaction effect difficult. Finally, it requires computing the cross derivative or cross difference. However, I report pooled probit and panel probit estimates in each specification after having computed a consistent estimator for the interaction effect for nonlinear model, and for the asymptotic variance of the estimated interaction effect according to the methodology presented in Ai and Norton (2003).

[30]In the robustness analysis I test the sensitivity of the results when clustering standard errors both at provincial and at regional level to allow for possible correlations of the unobserved features at a local level.

Figure 1: Probability of debt, income rank and local inequality (1)



(1) Figures report the effect on the probability of debt based on the probit pooled regression in Table 3.

household behaviour over time. Column 3 of Table 3 reports marginal effects from a random effects panel probit.[31] This model allows to shape in a more precise way differences in the households' behaviour, even though it greatly reduces the number of observations. Although the LPM/pooled probit and random-effects probit panel regression estimates are not directly comparable as regards the size of the coefficients, the results are substantially equivalent both in terms of the statistical significance and signs of the coefficients, as well as in their economic implications. However, at the bottom of column 3 in Table 3, I report a Likelihood Ratio test comparing the pooled probit with the random effects model. The test rejects the null hypothesis under which the random effect makes no contribution to the residual error of each equation and the same parameter values for each equation would result if the observations were all pooled over time. It follows that the panel specification should be considered the preferred one.

Column 4 of Table 3 shows that excluding the household's equivalised income, which may induce collinearity with the Icome Decile, does not alter results.

In order to distinguish the effect of regional income inequality from other regional characteristics, in the baseline specification I have used area fixed effects at one level of aggregation (macro-region) higher than the geographic area (region) used to construct the income distribution and the income inequality measure. To address the issue of other regional unobservables that may determine both regional inequality

[31] A fixed-effects probit model estimation would drop all households that exhibit no variation in the dependent variable over time. In other words, it would drop all the households which, during the whole period of analysis, are always either indebted or not indebted and would maintain only households switching borrowing status. The latter case would be outside of my modeling strategy of borrowing behaviour focussed, as it is quite standard in household finance literature, on the decision taken in every period on the allocation of resources and the amount of borrowing. More importantly, the adoption of a fixed-effects model would require a drastic drop in the number of observations and, in particular, leave with a modest number of households holding a debt.

and likelihood of debt, I run regressions with regional level fixed effects, which allows averaging out any regional time-invariant effect. Column 5 of Table 3 show that, despite it is no longer possible to separate the effect of Gini coefficient from other regional characteristics, the coefficient on the interaction term between the household's income decile and regional inequality is still significant and very similar in magnitude to the baseline results.

A relevant local credit market for households in Italy is considered to be a province Gobbi and Lotti (2004). Furthermore, provinces with relatively better-developed financial systems are likely to also have higher frequency of debt. Thus, including province fixed effects accounts for any such unobserved time-invariant location attributes, common to the credit market areas, that may affect household likelihood of debt. Results of specifications with province fixed effects reported in Column 6 of Table 3 are almost identical to the ones found with regional fixed effects, thus confirming the baseline findings.

In line with previous empirical evidence, I find that age has a non-linear effect: the probability of debt increases with age and decreases with age in a quadratic term. This result is compatible both with the demand channel (the need for a loan is strongest for youngest households and decreases beyond a certain age threshold) and with the supply channel (banks consider elder households safer borrowers until a certain age threshold when the longer life expectancy and increasing income profile of the younger prevail). The probability of debt is higher among well-educated households (head of household is a high-school), who are more likely to have rising income expectations and to afford lower entry costs due to a better financial education. Estimation's results confirm other evidence from descriptive statistics in Table 1. The frequency of debt increases with household size, is higher among married households and lower among self-employed ones whose income is subject to greater volatility.

5.2 Probability of demanding a loan

In order to single out the role of local inequality among determinants of loan demand, I estimate the probability of a household demanding a loan, using the specification of Equation 2. I present the results of the estimations in the left panel (columns 1 to 4) of Table 4. The estimates are practically the same for all the models employed: LPM, pooled probit and panel probit. The key finding is that both the estimated coefficients of $Gini_{irt}$ and $IncDecile_{irt} * Gini_{rt}$ are not significantly different from zero so that there is no evidence that demand-side factors related to local inequality levels matter for the borrowing decisions of households. In other words, both the "keeping up with the Joneses" and "the getting ahead of the Joneses" hypotheses would not find empirical evidence in data on loan applications. Thus, results point mainly toward channels operating through credit supply - namely through the banks' use of local income inequality as additional signal for identifying credit worthy customers.

5.3 Probability of being credit rationed

Next, I turn to supply side of the market by estimating the probability that a household's loan request is rejected, conditional on having applied for it, using the specification of Equation 3. Columns 6 to 8 in the right panel of Table 4 show estimates, respectively, of LPM and of probit regressions for the probability of being credit rationed.[32] In line with previous evidence on Italian data,[33] income increases the likelihood of application acceptance. In fact, the estimated coefficient of $IncDecile_{irt}$ is negative indicating that a higher household income rank is associated in the bank's evaluation with a higher ability to repay the debt. The important finding is that the coefficient of the interaction term $IncDecile_{irt} * Gini_{rt}$ is significantly negative, indicating that applications from top (low) income households in more (less) unequal regions are less (more) likely to be rejected than those from top (low) income households in less (more) unequal regions.

To control for the possible selectivity implied in excluding those households not asking for a loan, I have also estimated a Heckprobit model identified through the *Small City* variable. Results show that, in the case under scrutiny, the null hypothesis of no correlation between error terms of the two equations (demand and rationing probit models) is not rejected. In other words, coefficients of determinants of credit rationing presented in Table 4 are not biased because of sample selection.

Overall, the result for credit rationing is in line with the supply side interpretation of the results obtained in Section 4.1. It is also consistent with Coibion *et al.* (2014) model, and their empirical findings on US households debt accumulation, in which banks use an applicant's position in the local income distribution, along with the dispersion of that distribution, to make inferences about default risk. Despite this, it is worth stressing that my results empirically depart from theirs, mainly due to the differences between Italian and US household debt markets. First of all, I find that a higher income is associated with a higher likelihood of being indebted while they find that debt accumulation over the course of the early to mid-2000s in the US was, on average, greater for lower income households. More importantly, in my results the signalling channel seems to strengthen in the crisis period when credit supply conditions were tighter. Thus, the effect of local inequality on household debt appears to be larger the stronger is credit rationing in the system. Vice versa, Coibion *et al.* (2014) evidence supports the notion that the growth in household borrowing during the mid-2000s was driven in large part by credit supply expansions targeted at lower-income households. However, as said in Section 4.1, there could be manifold causes that explain how local income inequality is related to a signal of households' creditworthiness.

All in all, results suggest that once other household and location characteristics are controlled for, top-income households located in highly unequal regions are deemed safer borrowers than the corresponding ones residing in low-inequality regions, likely because of the more persistence of their income profile, which may suggest a higher capability of meeting debt repayments in the future.

[32]Since restricting the analysis to the households that have applied for a loan would require a drastic drop in the number of observations when using the panel dimension, unlike the case of loan demand, for credit rationing I do not estimate the panel probit model.

[33]See Crook and Hochguertel (2006); Magri (2007) and, more recently on mortgages market, Michelangeli and Sette (2016).

6 Extensions

Decomposition by type of debt I now consider if the results obtained are sensitive to the difference between types of debt: mortgages and consumer loans. I focus only on the probability of being indebted because the SHIW survey questions on loan demand and credit rationing do not allow for a distinction by types of debt. Then, for each type of loan, I reproduce the previous regressions and report results in Table 5. Columns 1 to 3 documents that the results for mortgages are almost identical to those found for total debt, albeit the parameter γ is estimated to be statistically significant only at 10% level for the random effects panel probit. Despite in Columns 4 and 5 the main effect of local inequality is not significant, I find still a statistically significant and strong relationship between local inequality and the probability of holding consumer loans across different income groups as expressed by the interaction effect $IncDecile_{irt} * Gini_{rt}$ as shown in particular in Column 6. All in all, results from the decomposition by type of debt indicate that both of them contribute to total debt patterns described above.

Pre-crisis vs crisis subsamples The dataset used covers a time span which allows comparisons between the periods before and during the crisis. In the years prior to the crisis, Italy experienced a fast growth in household credit market participation, even if not so strong as other countries. In the part of the latter period which is included in the data, there has been a significant growth in the housing market, driven by an increase in house prices and by relaxed credit conditions, as well as in consumer credit lending. These factors contributed to strengthen the path towards a convergence of Italian household credit market participation with the higher rates of participation in other countries. However, the financial crisis caused a drop in the demand for credit and a higher selectivity of banks in lending. This has affected the share of households with debt and the composition of borrowers with a rebalance towards high-income ones (see Table 1).[34] In light of these stylised facts, re-estimating the model (1) separately for the two sub-periods may help to better scrutinise the results presented on the effects of inequality on the probability of holding a debt. Tables 6 and 7 shows that evidence is stronger during the crisis period. In particular, Columns (1) to (3) of Table 6 show that during the pre-crisis period inequality still affected negatively probability of holding a debt, even though no significant asymmetric effect is found across different income groups. On the other hand, Columns (1) to (3) of Table 7 document that the results for the crisis period are almost identical to those found for whole timespan analysed (cf. Table 3).

It is easier to interpret the different pattern observed between the two periods by taking into account the behaviour for the different types of debt. Columns (4) and (5) of Table 6 show that before the crisis the differentiated effect of local inequality was full in place for the consumer loans while mortgages were completely unaffected by it. In contrast, the last two columns of Table 7 document how the asymmetric effect of inequality was fully common to both types of debt during the crisis period. In a nutshell, it can be said that evidence found in Section 5.1 is driven by both

[34] For a more in depth analysis of the recent evolution of credit market participation in Italy see Magri and Pico (2014).

forms of debt during the crisis period and only by consumer credit market before the crisis. Overall, these results seems in line with the idea that local inequality plays a role in affecting the likelihood of debt through the credit supply channel. In fact, before the crisis, when credit conditions were laxer, local inequality may not have affected mortgages market because of the collateralised nature of this form of debt. Despite mortgages represent much larger loan amounts than other forms of debt, in case of default banks may take possession and sell the secured property. Before the crisis, the housing market was in a expanding phase with rising prices and was easier for lenders to sell the property (in case of foreclosure) at a value sufficient to cover the remaining principal of the loan. Consumer loans, on the other hand, are mostly uncollateralised (with the exception of auto loans) and so may be considered by banks riskier, even though are much smaller in size. In the wake of the crisis, the tensions in the banks' funding availability and cost, the adverse shocks to households income and a depressed housing market led first to a tightening of credit standards and, subsequently, also to a reduction of the lending to Italian households. Hence, the incentive of banks to devote resources toward identifying applicants' underlying credit-worthiness should have strengthen, leading to a wider utilization of the information provided by local income inequality as found in Table 7.

7 Robustness analysis

In this Section, several robustness checks are considered. First of all, in order to account for any macro region-specific time trends that may influence household borrowing decisions, a specification with a full set of area-year dummies is tested. Results are reported in Table 8 and confirm the robustness of the baseline findings.

As is quite standard in the household finance literature, in my modeling strategy, households decide every period on the allocation of their resources and on borrowing. However, one may argue that for many households with mortgages outstanding in a given period, the decision to take up such loans was made many years prior to the interview. To examine the sensitivity of results to this issue, I have re-estimated the panel model for mortgages, focusing only on households that take up such loans (*i.e.* with switch borrowing status) during the period covered by the data. Specifically, I use the sample of households without outstanding mortgages in 2004 (*i.e.*, the initial observation period in the sample) and estimate the probability of taking up such a loan in any of the subsequent four waves. This panel model conditions on the same set of covariates as the ones used in the baseline specification (presented in Table 3). The estimated effects of local inequality on the likelihood of taking up a mortgage from this "inflow" sample are still significant, albeit at 10% confidence level, and have the same economic interpretation of the baseline specification (see Table 9).

Since in the baseline specification household-level controls are contemporaneous, one may be worried that this may introduce simultaneity bias. In Table 10 it is shown that the results are qualitatively unaffected when two-year[35] lagged household-level controls are replaced into the baseline specification.

Similarly to Coibion *et al.* (2014), I also consider a specification in which the

[35]It should be recalled that SHIW survey is carried out biannually so that lagged household controls referring to previous SHIW wave are two-year lagged.

measure of local income inequality as well as all the household-specific controls are fixed at the values of the beginning period (2004). This also removes the potential bias due to contemporaneous controls that may be influenced by the treatment effect. Moreover, such a specification can be interpreted as a "difference-in-differences" approach across income groups and regional inequality levels with the coefficient of the interaction between local income inequality and household income decile being the key parameter that determines whether such differences have been important. This change does not have significant impact on the results (cf. Table 11).

Standard errors of all the pooled estimates are clustered at household level in order to deal with the panel component of the data and correct for serial correlation. As said in Section 3, the SHIW sampling is in two stages: first municipalities are chosen from different strata and then households are selected at random. It follows that observations are independent across municipalities but there could be still within-municipality error correlation (*e.g.*, because of neighbourhood effects) affecting standard errors and, on top of that, unobserved provincial or regional effects. However, including fixed effects at different geographical level of aggregation generally does not control for all the within-cluster correlation of the error and one should still use the cluster-robust estimate of the variance matrix . Correcting standard errors for clustering first on municipality and then on province/region, the interpretation of the results does not change (for the sake of brevity, I do not report these results).

The Gini coefficient is sometimes criticised as being too sensitive to relative changes around the middle of the income distribution. Tables 12 and 13 show that the choice of Gini coefficient as income inequality indicator is unlikely to influence the results. The relationship between local income inequality, interacted with household income decile, and debt likelihood is still significant for various generalised entropy indicators which are sensitive to inequalities at the top or bottom of the income spectrum. Table 12 uses as income inequality measure the Theil Index, which is more sensitive than Gini coefficient to changes that affect the upper tail of the distribution, while Table 13 uses the mean logarithmic deviation which is more sensitive to changes in the lower tail. In all cases results are very similar to the ones of the baseline scenario, supporting the robustness of the findings under varying inequality measures. Furthermore, I have tested a functional form that employs quintiles, instead of deciles, to model the households' income ranks and the results are insensitive even to such a transformation.

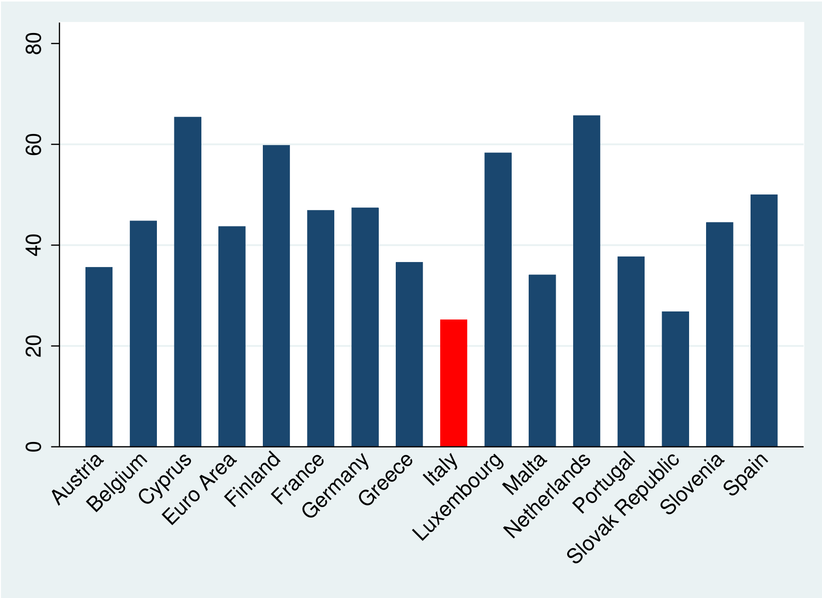
Finally, the inclusion of a wide range of controls in the baseline specification may raise multicollinearity concerns. To address this potential issue, I estimate a more parsimonious specification where location-specific controls are dropped. Results in Table 14 show that the findings are insensitive even to such a change.

8 Conclusion

The literature on household finance has only recently paid attention to the distribution of access to finance. Using Italian household-level data from Banca d'Italia's *Survey on Household Income and Wealth* combined with information on local inequality from *EU-Statistics on Income and Living Conditions* survey, this paper explored empirically the relationship between household debt and local income inequality highlighting the role that the belonging to different income groups plays in mediating this relationship. The analysis provides evidence that income inequality affects negatively the probability of being indebted. Moreover, it is shown that richer households living in regions highly unequal are relatively more likely indebted than, otherwise similar, richer households situated in low-inequality regions (and vice versa for poorer ones). The work also tested alternative views about the prevalence of demand or supply factors in shaping the interaction between inequality and household debt (namely the "keeping up with the Joneses" hypothesis versus the "signalling channel" one). In fact, local inequality does not seem to affect the likelihood to apply for a loan while greater inequality decreases the probability of loan application refusal for top income households (and increases for the poorer ones). Such results are consistent with models in which banks use an applicant's position in the local income distribution, along with the dispersion of that distribution, to make inferences about default risk; and are in line with the most recent survey-based evidence on US data according to which supply factors are more important than demand ones in explaining the mentioned result. These findings are found persistent after controlling for socio-demographic differences, different types of debt, unobserved individual heterogeneity thanks to panel data, and a number of robustness checks. Comparison between pre-crisis and crisis period indicates that, in line with the supply-side interpretation of the results, evidence is stronger during the latter one when credit supply conditions were particularly tight. This paper suggests that household income may be considered a stronger signal of creditworthiness in highly unequal regions because higher inequality implies less income mobility over time and a skewed access to investment opportunities and/or political influence. It follows that banks, which screen borrowers taking into account their capacity to meet their obligations in the future, are less prone to grant credit to poor households located in more unequal regions. In conclusion, inequality can become self-sustained as it produces unequal access to finance and ultimately unequal opportunities, which can reinforce any initial economic inequality.

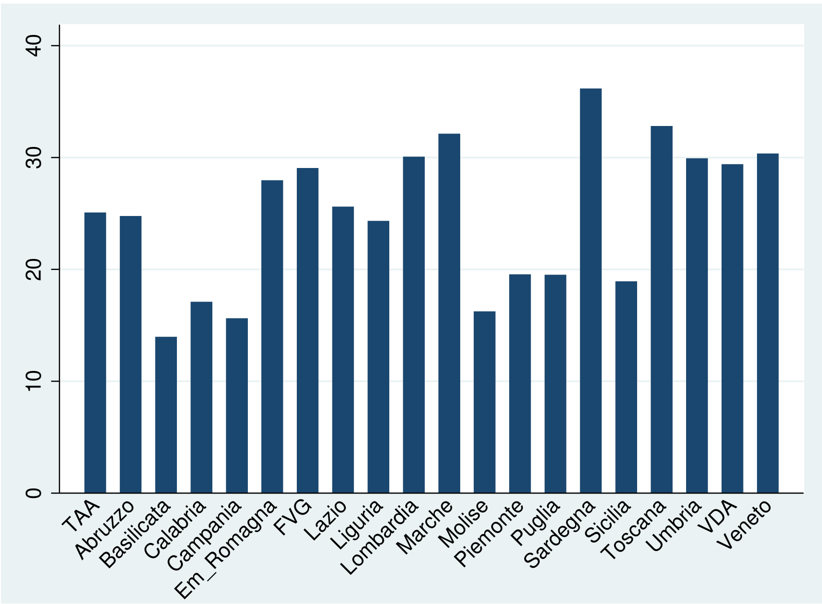
Tables and figures

Figure 2: Households with debt in Euro area countries (1)



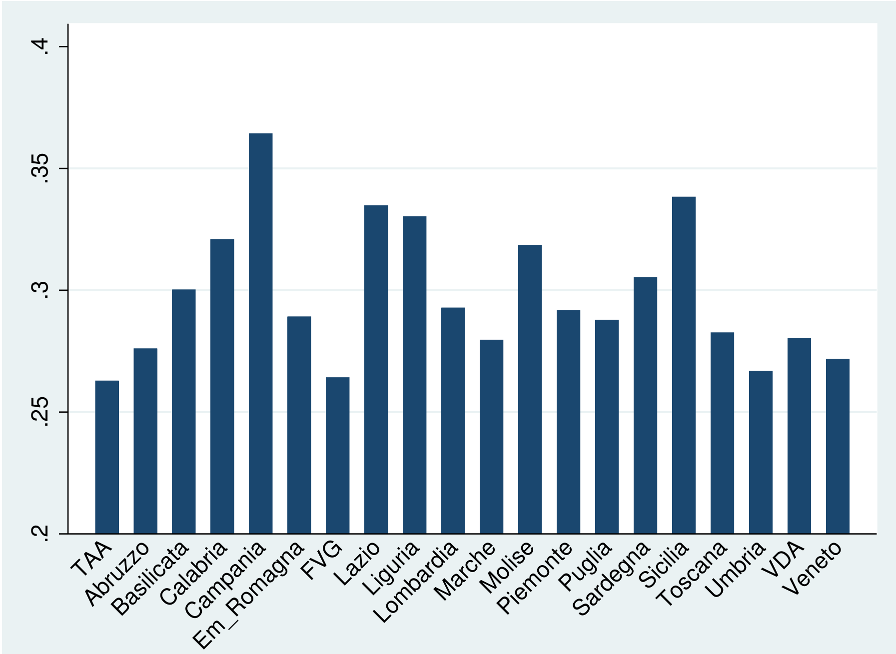
Source: ECB Household Finance and Consumption Survey (2013), Gambacorta *et al.* (2013). (1) Percentages.

Figure 3: Households with debt across Italian Regions (1)



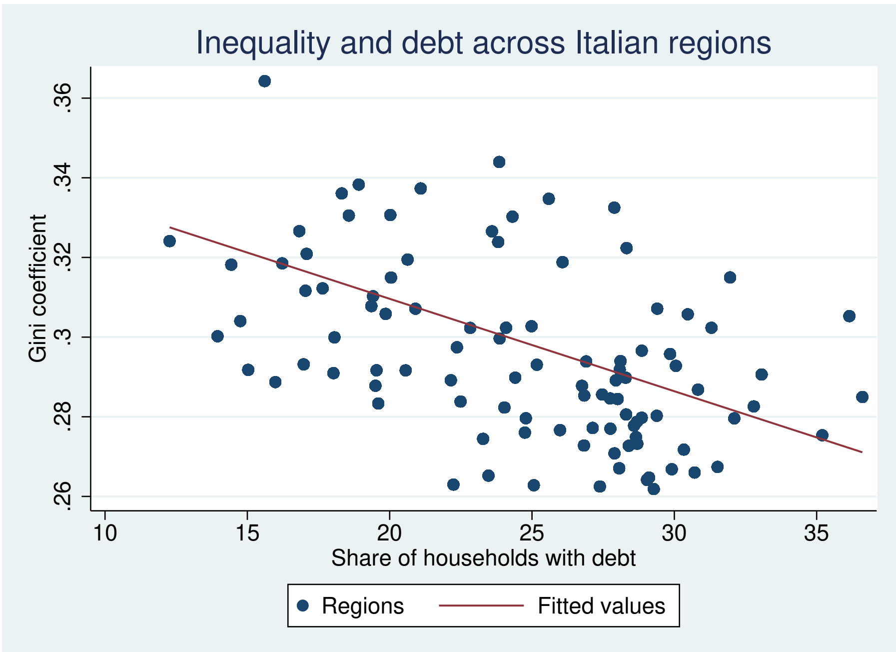
Source: Eu-Silc 2012. (1) Percentages.

Figure 4: Income inequality across Italian Regions (1)



Source: Eu-Silc 2012. (1) Gini coefficients of equivalised income.

Figure 5: Frequency of debt versus inequality (1)



Source: Eu-Silc (waves 2004, 2006, 2008, 2010, 2012). (1) The frequencies are weighted and refer to the whole sample of households.

Table 1: Percentage of households with debt for personal needs by social and economic characteristics (1)

	2004	2006	2008	2010	2012	Number of households (2)
Sex of the head						
Male	25.7	24.9	26.0	23.4	23.0	5,398
Woman	13.2	16.4	18.7	15.9	15.2	2,654
Age of the head						
Less than 35 years	30.8	30.1	31.5	29.3	22.5	503
35 to 44 years	34.2	36.5	37.8	33.0	32.8	1,137
45 to 54 years	31.4	26.2	34.1	32.0	30.6	1,664
55 to 64 years	19.6	22.8	22.3	19.4	18.2	1,555
65 years or older	4.9	6.3	6.3	5.2	6.5	3,193
Education of the head						
Primary school or without education	9.0	9.0	9.0	7.6	6.3	2,071
Junior high school	23.0	23.4	27.1	23.6	22.0	2,804
High school	31.2	30.3	31.3	26.7	27.1	2,146
Degree or more	28.4	27.1	29.3	27.6	25.9	1,031
Job status of the head						
Employee	31.3	31.5	34.0	33.5	30.3	3,240
Self-employed	31.6	29.4	31.4	21.5	24.3	824
Non worker	7.8	9.4	9.7	7.9	7.8	3,988
Quartiles of equivalised income						
First quartile	13.5	14.8	17.7	15.8	13.7	1,699
Second quartile	19.9	17.5	19.6	18.2	17.8	2,067
Third quartile	23.3	24.4	27.4	22.6	23.0	2,146
Fourth quartile	29.5	31.4	29.6	26.7	25.5	2,140
Quartiles of equivalised net wealth						
First quartile	18.9	18.6	20.7	19.3	16.8	1,795
Second quartile	26.1	24.2	30.8	28.4	27.5	1,702
Third quartile	21.2	23.8	23.7	18.5	21.7	2,150
Fourth quartile	21.7	23.0	21.2	19.0	16.5	2,405
Size of the municipality						
Up to 20,000 inhabitants	22.3	23.4	25.0	20.4	19.4	2,005
More than 20,000 inhabitants	21.5	21.4	22.7	21.6	21.2	6,047
Geographical areas						
North West	24.4	25.0	26.8	20.6	19.3	1,913
North East	24.5	24.5	27.2	21.7	22.6	1,586
Centre	20.8	24.7	19.7	25.1	25.6	1,714
South and Islands (Mezzogiorno)	18.6	16.8	21.5	18.4	16.7	2,839
Number of households' members						
1 member	11.1	14.9	12.7	10.3	10.4	2,160
2 members	16.4	15.8	18.9	14.6	15.0	2,526
3 members	28.1	27.7	31.4	27.6	28.0	1,550
4 members	35.7	32.4	35.8	35.9	32.8	1,330
5 and more members	27.6	34.0	38.0	33.6	32.2	486
Number of income earners						
1 earner	15.5	18.3	18.2	15.3	15.5	4,119
2 earners	27.7	25.0	28.8	26.3	25.8	3,200
3 earners	27.7	29.7	28.7	25.7	25.1	597
4 earners and more	37.8	29.3	33.3	27.5	22.7	136
Total	21.9	22.3	23.7	21.0	20.3	8,052

Source: *Survey of Household Income and Wealth.* (1) The frequencies are weighted and refer to the whole sample; the 5 categories included in the debt for personal needs are: Buildings, Other real assets, Vehicles, Durable goods, Non-durable goods.(2) Number of households in 2012 wave.

Table 2: Correlations among regressors

	Gini	Income Dec.	Inc.Dec. *Gini	Age	Age squared	Educ.	Household size	Married	Self empl.	Small city	Dissaving	Bad debts	Housing prices	Loans to hh	Equiv. Income
Gini	1.00														
Income Decile	-0.04	1.00													
Income Decile*Gini	0.04	0.03	1.00												
Age	0.02	0.05	0.02	1.00											
Age squared	0.02	0.04	0.02	0.99	1.00										
Education	-0.07	0.39	0.04	-0.28	-0.29	1.00									
Households size	0.12	-0.10	-0.06	-0.22	-0.25	0.07	1.00								
Married	0.06	0.00	-0.02	0.15	0.12	-0.03	0.52	1.00							
Self-employed	-0.01	0.12	-0.02	-0.10	-0.12	0.08	0.10	0.05	1.00						
Small city	-0.17	-0.04	0.01	-0.02	-0.02	-0.08	0.03	0.01	0.03	1.00					
Dissaving	0.11	-0.37	-0.04	-0.10	-0.10	-0.09	-0.01	-0.03	0.02	-0.04	1.00				
Ratio of new bad debts	0.35	-0.00	0.00	0.04	0.03	0.00	0.06	0.04	-0.01	-0.10	0.09	1.00			
Housing prices	-0.04	-0.01	-0.00	-0.04	-0.04	-0.05	0.01	-0.01	-0.00	-0.00	-0.04	-0.52	1.00		
Loans to households	0.31	0.00	-0.00	0.03	0.03	0.01	0.05	0.04	-0.01	-0.09	0.07	0.91	-0.50	1.00	
Equivalised Income	-0.22	0.83	-0.03	0.06	0.05	0.41	-0.15	-0.01	0.15	-0.01	-0.33	-0.10	-0.05	-0.08	1.00

Note: statistics are computes on the SHIW sample selection used for the cross-sections estimates reported in Table 3. See Section 3.1 for more details.

Table 3: Different estimates of Pr(loan>0) - comparison Baseline

	(1) LPM	(2) Pooled Probit	(3) RE Panel Probit	(4) RE Panel Probit	(5) RE Panel Probit	(6) RE Panel Probit
Income Decile	0.02***	0.02***	0.02***	0.03***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.51**	-0.54**	-1.14***	-1.15***	-0.60	-0.62
	(0.22)	(0.23)	(0.39)	(0.39)	(0.60)	(0.59)
Income Decile*Gini	0.18***	0.19***	0.29***	0.26***	0.28***	0.23**
	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)	(0.10)
Equivalised Income	0.00	0.00	0.00***		0.00***	0.00*
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
Age	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Elementary school	0.00	-0.00	0.05**	0.04*	0.05*	0.04
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Middle school	-0.02**	-0.02**	-0.00	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
University	-0.04**	-0.04***	-0.04	-0.03	-0.05*	-0.05*
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
Households size	0.03***	0.03***	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Married	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Self-employed	-0.05***	-0.05***	-0.05***	-0.05**	-0.05***	-0.05**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Small city	0.00	0.00	-0.03	-0.03	-0.03	-0.04**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Dissaving	0.12***	0.12***	0.14***	0.14***	0.14***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ratio of new bad debts	0.01	0.02	-0.00	-0.01	0.08*	0.08*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Housing prices by region	-0.01***	-0.01***	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Loans to household	0.05	0.05	0.17	0.17	0.08	0.04
	(0.10)	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)
Macro-region FE	Yes	Yes	Yes	Yes	No	No
Region FE	No	No	No	No	Yes	No
Province FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	7762	7762	7720
R2/Pseudo R2	0.08	0.07				
Predicted Probability		0.253	0.153	0.154	0.153	0.155
LR Test (*p-value*)			0.000	0.000	0.000	0.000

Note: The Table reports marginal effects (and associated standard errors) from the following three binary regressions used to model the probability of having an outstanding loan: (1) a linear probability model, estimated via OLS, (2) a nonlinear probability model, estimated via pooled probit, and (3) to (6) a nonlinear probability model, estimated via panel probit random effect estimation. Marginal effects are expressed at the mean value of the independent variables and, in the case of interaction terms in nonlinear models, are computed by taking into account cross derivatives Ai and Norton (2003). A likelihood-ratio test on the significance of the panel level variance component is included at the bottom of the output under the null that the panel-level variance component is unimportant, and the panel estimator is not different from the pooled estimator. Standard errors are corrected for heteroscedasticity and (in the pooled estimations) clustered at the household level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 4: the probability of demanding a loan and of being credit rationed

	Loan Demand					**Credit rationing**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LPM	Pooled Probit	RE Panel Probit	RE Panel Probit	RE Panel Probit	LPM	Pooled Probit	Pooled Probit
Income Decile	0.00	0.00	0.00	0.00*		-0.01	0.01	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)
Gini	0.14	0.15	0.01	0.01	0.01	1.26	0.66	0.99
	(0.13)	(0.12)	(0.15)	(0.15)	(0.15)	(0.77)	(0.75)	(0.76)
Income Decile*Gini	0.03	0.03	-0.01	-0.01	-0.01	-0.45**	-0.44**	-0.32*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.19)	(0.19)	(0.19)
Equivalised Income	0.00	0.00	-0.00		0.00	-0.01**	-0.02**	
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.01)	
Age	-0.00	-0.00	-0.00	-0.00	-0.00	-0.02*	-0.01*	-0.02*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Age squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Elementary school	0.00	0.00	0.02**	0.02**	0.02**	0.12**	0.10**	0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)
Middle school	-0.00	-0.00	-0.00	-0.00	-0.00	0.08**	0.07**	0.08**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
University	-0.01*	-0.01*	-0.01	-0.01	-0.01	-0.05*	-0.15***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)
Household size	0.01***	0.01***	0.01**	0.01**	0.01*	-0.03*	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Married	0.00	0.01	0.01*	0.01*	0.01*	-0.04	-0.04	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Self-employed	0.00	0.01	-0.00	-0.00	-0.00	0.08**	0.08**	0.07**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Small city	-0.01*	-0.01*	-0.01	-0.01	-0.01			
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)			
Dissaving	0.05***	0.04***	0.03***	0.03***	0.03***			
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)			
Housing prices	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
New bad debts						0.14**	0.14***	0.14***
						(0.06)	(0.05)	(0.05)
Macro-region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	20683	20683	5071	5071	5071	1575	1575	1575
R2/Pseudo R2	0.02	0.03				0.17	0.19	0.18
Predicted Probability		0.05	0.03	0.03	0.03		0.15	0.16
LR Test (*p-value*)			0.00	0.00	0.00			

Note: The left panel of the Table reports marginal effects (and associated standard errors) from the following three binary regressions used to model the probability of demanding a loan: (1) a linear probability model, estimated via pooled OLS, (2) a nonlinear probability model, estimated via pooled probit, and (3)-(5) a nonlinear probability model, estimated via panel probit random effect estimation. The right panel of the Table reports marginal effects (and associated standard errors) from the following three binary regressions used to model the probability of demanding a loan and being credit rationed: (6) a linear probability model, estimated via pooled OLS, (7)-(8) a nonlinear probability model, estimated via pooled probit. Marginal effects are expressed at the mean value of the independent variables and, in the case of interaction terms in nonlinear models, are computed by taking into account cross derivative Ai and Norton (2003). A likelihood-ratio test on the significance of the panel level variance component is included at the bottom of the output under the null that the panel-level variance component is unimportant, and the panel estimator is not different from the pooled estimator. Standard errors are corrected for heteroscedasticity and (in the pooled estimations) clustered at the household level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 5: Different estimates of Pr(loan>0) - decomposition by type of debt

	Mortgages			**Consumer Loans**		
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	Pooled Probit	RE Panel Probit	LPM	Pooled Probit	RE Panel Probit
Income Decile	0.01***	0.01***	0.00**	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.49***	-0.54***	-0.11	-0.19	-0.18	-0.82***
	(0.18)	(0.18)	(0.08)	(0.18)	(0.18)	(0.25)
Income Decile*Gini	0.12**	0.16***	0.03*	0.16***	0.15***	0.18***
	(0.05)	(0.05)	(0.02)	(0.05)	(0.05)	(0.07)
Equivalised Income	0.00**	0.00	0.00**	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	29282	29282	7762
R2/Pseudo R2	0.06	0.09		0.04	0.05	
Predicted Probability		0.13	0.01		0.14	0.09
LR Test (*p-value*)			0.00			0.00

Note: The Table reports marginal effects (and associated standard errors) from the following three binary regressions used to model the probability of having, respectively, outstanding mortgage or consumer loans: (1) and (4) a linear probability model, estimated via OLS, (2) and (5) a nonlinear probability model, estimated via pooled probit, and (3) and (6) a nonlinear probability model, estimated via panel probit random effect estimation. Marginal effects are expressed at the mean value of the independent variables and, in the case of interaction terms in nonlinear models, are computed by taking into account cross derivatives Ai and Norton (2003). A likelihood-ratio test on the significance of the panel level variance component is included at the bottom of the output under the null that the panel-level variance component is unimportant, and the panel estimator is not different from the pooled estimator. Standard errors are corrected for heteroscedasticity and (in the pooled estimations) clustered at the household level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 6: Different estimates of Pr(loan>0) - sample split: pre-crisis period (2004-2008)

	(1)	(2)	(3)	(4)	(5)
	Total Debt			Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.02***	0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.76***	-0.85***	-1.45***	-0.14*	-0.72***
	(0.30)	(0.31)	(0.41)	(0.08)	(0.27)
Income Decile*Gini	0.12	0.15	0.17	0.01	0.22***
	(0.09)	(0.09)	(0.11)	(0.02)	(0.07)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	17794	17794	7113	7113	7113
R2/Pseudo R2	0.08	0.08			
Predicted Probability		0.26	0.16	0.01	0.09
LR Test (*p-value*)			0.00	0.00	0.00

Note: see Table 3.

Table 7: Different estimates of Pr(loan>0) - sample split: crisis period (2010-2012)

	(1)	(2)	(3)	(4)	(5)
	Total Debt			Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.01***	0.00**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.53	-0.51	-0.76**	-0.07*	0.41**
	(0.33)	(0.34)	(0.31)	(0.03)	(0.17)
Income Decile*Gini	0.25***	0.25***	0.25***	0.02**	0.09**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.04)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	11488	11488	6496	6496	6496
R2/Pseudo R2	0.07	0.07			
Predicted Probability		0.242	0.098	0.002	0.049
LR Test (*p-value*)			0.000	0.000	0.000

Note: see Table 3.

Table 8: Different estimates of Pr(loan>0) - specification with interaction Macro-region x Year FE

	(1)	(2)	(3)	(4)	(5)
	Total Debt			Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.02***	0.00**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.60***	-0.64***	-1.04***	-0.11	-0.70***
	(0.23)	(0.24)	(0.39)	(0.07)	(0.24)
Income Decile*Gini	0.18***	0.19***	0.28***	0.03*	0.17***
	(0.06)	(0.06)	(0.10)	(0.02)	(0.07)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Macro-region x Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	7762	7762
R2/Pseudo R2	0.08	0.07			
Predicted Probability		0.253	0.152	0.011	0.083
LR Test (*p-value*)			0.000	0.000	0.000

Note: see Table 3. With respect to the baseline scenario, this specification includes the interaction between macro-region and time fixed effects to account for any location-specific time trends that may influence individual borrowing decisions.

Table 9: Estimates of Pr(Mortgage>0) - only households not indebted in 2004

	(1)
	RE Panel
	Probit
Mortgage	
Income Decile	0.08**
	(0.04)
Gini	-4.90
	(3.31)
Income Decile*Gini	1.66*
	(0.86)
Equivalised Income	0.02*
	(0.01)
Household controls	Yes
Location controls	Yes
Macro-region FE	Yes
Year FE	Yes
N. of observations	5034
LR Test (*p-value*)	0.000

Note: see Table 3. In this specification only households that were not indebted at the beginning of the period of analysis (2004) are considered. In this way the risk of considering decisions taken many years prior the interview is reduced.

Table 10: Different estimates of Pr(loan>0) - specification with fully lagged controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total Debt		Mortgages	Consumer Loans	Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel	Pooled	Pooled
	LPM	Probit	Probit	Probit	Probit	Probit	Probit
Income Decile	0.00	0.01	0.01	0.00	0.00	0.00	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.73*	-0.76*	-0.83*	-0.09	-0.40	-0.56	-0.41
	(0.44)	(0.45)	(0.45)	(0.07)	(0.28)	(0.37)	(0.31)
Income Decile*Gini	0.25**	0.27**	0.37***	0.03*	0.20**	0.19*	0.11
	(0.12)	(0.12)	(0.12)	(0.02)	(0.08)	(0.10)	(0.08)
Equivalised Income	0.00*	0.00*	0.00	0.00	-0.00	0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	12244	12244	5946	5946	5946	12244	12244
R2/Pseudo R2	0.06	0.05				0.09	0.04
Predicted Probability		0.260	0.145	0.007	0.082	0.125	0.144
LR Test (*p-value*)			0.000	0.000	0.000		

Note: see Table 3. To avoid potential simultaneity bias due to the contemporaneous household-level controls, in this specification household-level controls are replaced with their value at previous SHIW wave (i.e. they are two-year lagged).

Table 11: Different estimates of Pr(loan>0) - all controls from year = 2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total Debt		Mortgages		Consumer Loans	
		Pooled	RE Panel	Pooled	RE Panel	Pooled	RE Panel
	LPM	Probit	Probit	Probit	Probit	Probit	Probit
Income Decile	0.01***	0.01***	0.02**	0.01***	0.01***	0.01***	0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Gini	-0.41	-0.48	-0.58	-0.57*	-0.07	-0.04	-0.36
	(0.37)	(0.39)	(0.47)	(0.33)	(0.10)	(0.27)	(0.27)
Income Decile*Gini	0.25**	0.27***	0.52*	0.15*	0.10	0.21***	0.35*
	(0.10)	(0.11)	(0.32)	(0.09)	(0.07)	(0.07)	(0.19)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	No	No	No	No	No	No	No
Macro-region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	14427	14427	7755	14427	7755	14427	7755
R2/Pseudo R2	0.07	0.07		0.07		0.05	
Predicted Probability		0.252	0.158	0.123	0.126	0.143	0.089
LR Test (*p-value*)			0.000		0.000		0.000

Note: see Table 3. In order to avoid treatment effect in this specification the Gini coefficients and all household-specific controls are from the beginning of the period of analysis (2004).

Table 12: Different estimates of Pr(loan>0) - different measures of inequality: Theil Index

	(1)	(2)	(3)	(4)	(5)
		Total Debt		Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.01***	0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Theil Index	-0.43***	-0.47***	-0.59***	-0.11**	-0.36**
	(0.13)	(0.14)	(0.23)	(0.05)	(0.11)
Income Decile *Theil Index	0.10***	0.12***	0.13*	0.01	0.09*
	(0.04)	(0.04)	(0.07)	(0.01)	(0.05)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	7762	7762
R2/Pseudo R2	0.08	0.07			
Predicted Probability		0.254	0.154	0.012	0.086
LR Test (*p-value*)			0.000	0.000	0.000

Note: The Table reproduces the results in Table 3 using the Theil Index measure of inequality rather than the Gini coefficient.

Table 13: Different estimates of Pr(loan>0) - different measures of inequality: Mean Logarithmic Deviation

	(1)	(2)	(3)	(4)	(5)
		Total Debt		Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.02***	0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mean Logarithmic Deviation	-0.45***	-0.47***	-0.65**	-0.10*	-0.45**
	(0.17)	(0.18)	(0.29)	(0.06)	(0.19)
Income Decile*Mean Log. Dev.	0.14***	0.15***	0.27***	0.03**	0.15***
	(0.04)	(0.05)	(0.08)	(0.02)	(0.05)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	7762	29282
R2/Pseudo R2	0.08	0.07			
Predicted Probability		0.254	0.154	0.012	0.086
LR Test (*p-value*)			0.000	0.000	0.000

Note: The Table reproduces the results in Table 3 using the Mean Logarithmic Deviation measure of inequality rather than the Gini coefficient.

Table 14: Different estimates of Pr(loan>0) - parsimonious specification with only household-level controls

	(1)	(2)	(3)	(4)	(5)
		Total Debt		Mortgages	Consumer Loans
		Pooled	RE Panel	RE Panel	RE Panel
	LPM	Probit	Probit	Probit	Probit
Income Decile	0.02***	0.02***	0.02***	0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini	-0.35	-0.36	-1.01***	-0.25*	-0.75***
	(0.22)	(0.23)	(0.38)	(0.14)	(0.26)
Income Decile*Gini	0.18***	0.19***	0.28***	0.06*	0.18***
	(0.06)	(0.06)	(0.10)	(0.03)	(0.07)
Household controls	Yes	Yes	Yes	Yes	Yes
Location controls	No	No	No	No	No
Macro-region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N. of observations	29282	29282	7762	7762	7762
R2/Pseudo R2	0.07	0.07			
Predicted Probability		0.254	0.154	0.032	0.104
LR Test (*p-value*)			0.000	0.000	0.000

Note: see Table 3. With respect to the baseline scenario, this specification does not consider location-specific controls

Appendix A

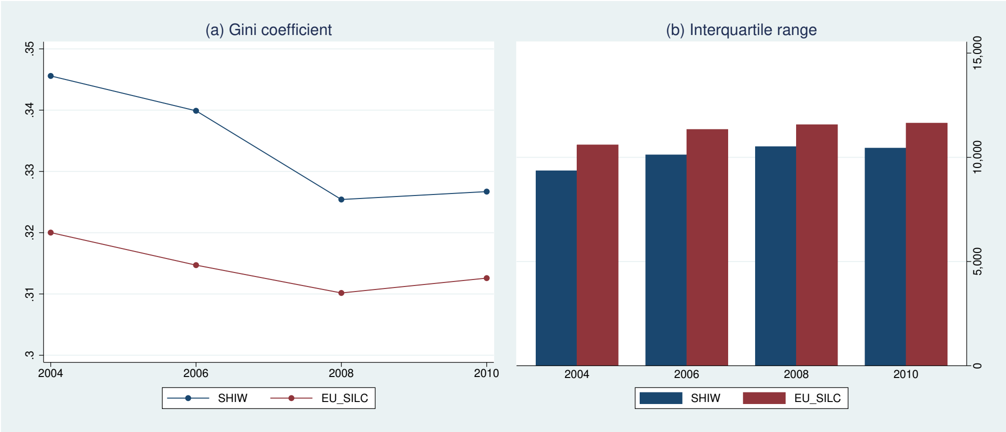
Despite the discrepancy in absolute levels of equivalised household incomes, which are (on average) smaller for SHIW[36], in figures A1 (a)-(d) it is observed a very similar distribution of income among quartiles. Figures A2 (a)-(b) compare, respectively, the Gini coefficient and the Interquartile range over the time period 2004-2010. Both indices show the same time pattern and a strong correlation between the two sources of data (0.93 in the case of Gini coefficient and 0.99 for the Interquartile range).

Figure A1: Quartiles of equivalised income (1)

Source: Eu-Silc and SHIW. (1) Monetary disposable income.

[36]The difference is mainly due to the different methods adopted by the two surveys to minimise the underestimation of self-employment incomes. For a more in depth analysis see Sierminska and Medgyesi (2013); Ciampalini *et al.* (2009); Di Marco (2006).

Figure A2: Inequality indices (1)



Source: Eu-Silc and SHIW. (1) Monetary disposable equivalised income.

Table A1: Summary statistics

Variable	Mean	St Dev	Percentiles				
			10	25	50	75	90
		Panel A: *Survey of Household Income and Wealth*					
Age of the head of household	48.18	12.16	32	39	47	58	66
Household size	2.74	1.23	1	2	3	4	4
Education	2.47	0.88	1	2	2	3	4
Unemployed	0.02	0.13	0	0	0	0	0
Self-employed	0.20	0.40	0	0	0	0	1
Married	0.64	0.48	0	0	1	1	1
Debt	0.27	0.44	0	0	0	1	1
Mortgages	0.15	0.36	0	0	0	0	1
Consumer credit	0.15	0.36	0	0	0	0	1
Equivalised income	15,581	8,754	6,377	9,421	14,090	19,821	26,485
Total debt	10,750	33,383	0	0	0	1,120	32,000
		Panel B: *EU-Statistics on Income and Living Conditions*					
Age of the head of household	48.83	12.29	32	39	49	59	66
Household size	2.67	1.28	1	2	3	4	4
Education	2.48	0.91	1	2	3	3	4
Unemployed	0.04	0.19	0	0	0	0	0
Self-employed	0.10	0.30	0	0	0	0	0
Equivalised income	17,754	10,072	7,062	10,727	16,089	22,513	30,380

Note: The sample is restricted to the households with 20-70 year old head of household. The statistics are calculated using sampling weights. The Table shows the statistics from the sample restricted to observations with positive equivalised income. The sample is further restricted to remove outliers. See text for more details. Total debt is the sum of Mortgages and Consumer credit. The number of observations in Panel A is 29,282 from the waves 2004, 2006, 2008, 2010, 2012 of SHIW. The number of observations in Panel B is 75,177 from the waves 2004, 2006, 2008, 2010, 2012 of EU-SICL.

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