BANCA D'ITALIA
EUROSISTEMA

# Questioni di Economia e Finanza

(Occasional Papers)

## Modelling households' financial vulnerability with consumer credit and mortgage renegotiations

by Carmela Aurora Attinà, Francesco Franceschi and Valentina Michelangeli

November 2019

Number 531

BANCA D'ITALIA
EUROSISTEMA

# Questioni di Economia e Finanza

(Occasional Papers)

## Modelling households' financial vulnerability with consumer credit and mortgage renegotiations

by Carmela Aurora Attinà, Francesco Franceschi and Valentina Michelangeli

Number 531 – November 2019

*The series* Occasional Papers *presents studies and documents on issues pertaining to the institutional tasks of the Bank of Italy and the Eurosystem. The* Occasional Papers *appear alongside the* Working Papers *series which are specifically aimed at providing original contributions to economic research.*

*The* Occasional Papers *include studies conducted within the Bank of Italy, sometimes in cooperation with the Eurosystem or other institutions. The views expressed in the studies are those of the authors and do not involve the responsibility of the institutions to which they belong.*

*The series is available online at www.bancaditalia.it .*

ISSN 1972-6627 (print)
ISSN 1972-6643 (online)

*Printed by the Printing and Publishing Division of the Bank of Italy*

**MODELLING HOUSEHOLDS' FINANCIAL VULNERABILITY WITH CONSUMER CREDIT AND MORTGAGE RENEGOTIATIONS**

by Carmela Aurora Attinà, Francesco Franceschi and Valentina Michelangeli*

## Abstract

Strong growth in consumer credit and widespread recourse to mortgage renegotiations observed since 2015 have affected households' ability to repay their loans. In this paper we explore a novel way of accounting for these trends, by extending the Bank of Italy microsimulation model of households' financial vulnerability. The extension provides a more accurate assessment of the financial stability risks stemming from the household sector. Consumer credit growth drives an increase in the share of vulnerable households, but has limited effects on the overall debt at risk. Mortgage renegotiations contribute to a decrease in households' vulnerability.

**JEL Classifications**: C1, G2.
**Keywords**: vulnerability, consumer credit, mortgage renegotiations
**DOI**: 10.32057/0.QEF.2019.531

## Contents



* Bank of Italy, Directorate General for Economics, Statistics and Research. We thank Francesco Columba, Antonio Di Cesare, Paolo Finaldi Russo, Giorgio Gobbi, Silvia Magri, Sabrina Pastorelli, Valerio Paolo Vacca for their useful comments.

## 1. Introduction

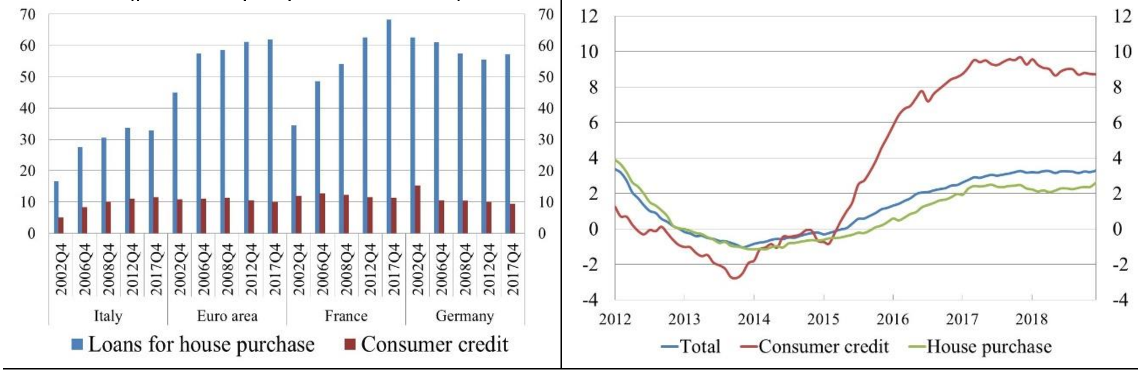
In Italy, risks to financial stability stemming from households' debt are limited. Italian households are less indebted than European ones, though their debt-to-disposable income ratio has increased significantly since the beginning of the last decade, reaching 61.3 per cent in 2017 (37.2 per cent in 2002).[2] While mortgage indebtedness has remained quite low by international comparison (Figure 1a), consumer credit[3] has expanded considerably in recent years (from -1.0 per cent in 2013 to 9.0 per cent in 2018; Figure 1b)[4] and, as a share of disposable income, is very close to that of other countries in the euro area.

**Figure 1**

**Mortgages and consumer credit**

(*percentages*)

a) Mortgages and consumer credit (*per cent of disposable income*) | b) Annual growth rate of bank loans to households




Sources: Panel a) National accounts; Panel b) Supervisory reports.

Despite the significant expansion in loans to households, the debt service to income ratio (DSR) has not risen much. In fact, the impact of higher debt on loan installments has been mitigated in recent years by exceptionally low interest rates. Households have benefited from low rates by, amongst other things, renegotiating the terms of their mortgages,[5] particularly in 2015 and 2016 (Figure 2a). Low rates and renegotiations have

[2] The first year for which we have detailed data for all countries.

[3] A long list of banking and other financial products falls under the definition of consumer credit. According to the Italian banking law and to Directive 2008/48/EC on credit agreements for consumers, consumer credit is any loan issued for personal needs other than those with the following characteristics: i) involving amounts below €200 or above €75,000; ii) granted free of interest, without other charges, or in the form of an overdraft facility to be repaid within 1 month; iii) secured by a mortgage; iv) concluded for the purchase of land or real estate; v) or lease or rental agreements where there is no obligation to purchase; vi) resulting from a judicial ruling; vii) linked to loans granted to a restricted group from within the general public.

[4] See Magri et al., (2019) and Bank of Italy (2018) for a more detailed description of recent trends.

[5] We can distinguish between three different types of mortgage renegotiations: 'rinegoziazione' (variation in some mortgage characteristics, such as the duration, type of rate, but not the amount, with the same bank), 'surroga' (portability, moving the mortgage from one bank to another), and 'sostituzione' (mortgage cancellation and formalization of a new loan with the same or a different bank). More information on consumers' rights can be found here: 'Bank of Italy Guides. Buying a home: Mortgages made easy.'

helped improve debt sustainability. Greater selectivity by banks in granting loans with respect to the pre-crisis levels[6] has also contributed to the decrease in the new non-performing loan ratio, which has fallen from the record high of 2009 for both mortgages and consumer loans (Figure 2b).[7]

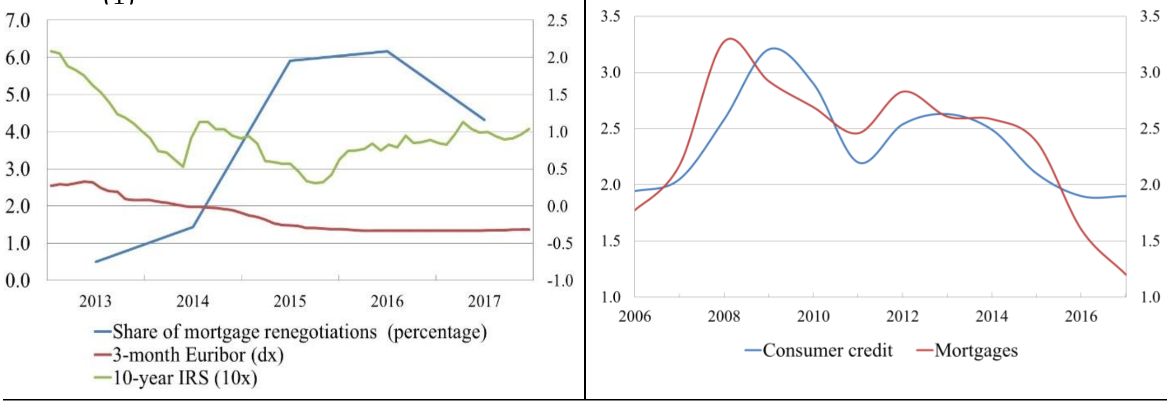
**Figure 2**

**Mortgage renegotiations and risks**

(*percentages*)

a) Mortgage renegotiations and interest rates (1)

b) New non-performing loan rate




Sources: Panel (a), Supervisory reports and MIR data; Panel b) Supervisory reports for mortgages and CRIF data for consumer credit.

(1) The share of mortgage renegotiations is given by the sum of the total amount of the mortgages whose contract terms have been revised over the previous period's stock of mortgages

The evidence suggests that in order to monitor the risks associated with the household sector in a timely manner, a model that projects the evolution of financially vulnerable households (i.e. those with a DSR above 30 per cent and income below the median of the population) should account for both consumer credit dynamics and the possibility of revising the contract terms through mortgage renegotiation. Growth in consumer loans may lead to an increase in vulnerability, especially for those households that already have a mortgage. At the same time, renegotiations act in the opposite direction by reducing loan installments. To capture these different forces affecting households' vulnerability, in this paper we propose an extension of the Bank of Italy's microsimulation model developed by Michelangeli and Pietrunti (2014).[8]

Building on the biannual information on households' characteristics and loan types provided in the Bank of Italy's Survey on Household Income and Wealth (SHIW), we

---

[6] Bank selectivity and households' choices have driven changes in the distribution of debt across income quartiles. In 2010, consumer loans were rather evenly distributed across household income groups (Figure A.1 in the Appendix). This implied that low-income households were proportionally bearing a much higher consumer debt than high-income ones. However, this situation has partially changed in recent years, as the share of consumer credit held by high-income households has progressively increased. Similarly, in 2016 the vast majority of mortgages were concentrated among households with income above the median of the population.

[7] In terms of stocks, in 2017 non-performing loans (NPLs) for both types of loan decreased with respect to the peak, but they still remained quite sizeable (Table A.1 in the Appendix).

[8] This microsimulation model accounts for mortgage and income dynamics.

allow the amount and cost of consumer loans to change over time according to the higher-frequency macroeconomic data. This implies, for instance, that a rapid increase in consumer loans can be rapidly taken into account in the microsimulation model. More specifically, the projection of consumer credit is made in three steps: estimation of household participation, forecast of the total amount of consumer credit, computation of the installment paid by each household. While we take an empirical approach for the first two steps, we impose some structure for the third one, assuming a standard amortization scheme. For mortgage renegotiations, we introduce a simple heuristic, according to which households revise their contract terms when they pay an interest rate that is significantly above current market rates. This gives a share of households renegotiating their mortgage that is consistent with the evidence from the survey data.

Significant innovations have altered the model's dynamics and improved the accuracy of its projections. First, the backtest exercises run over the periods 2012-14 and 2014-16 show that with the new features, the model is better able to replicate (out of sample) the decline in vulnerability observed in the survey data. In particular, adding the possibility of renegotiating the mortgage terms turns out to be crucial for reproducing the downward trend observed between 2012 and 2016. Second, the new model allows us to assess how sustained growth in consumer credit would affect households' debt sustainability. Third, more flexible stress tests can be run.[9]

Finally, we provide a brief analysis of how the share of vulnerable households and debt at risk would change if we were to define as vulnerable all households with a DSR above 30 per cent (i.e. not only those with income below the median of the population). While households with income below the median are the ones at higher risk of default, this broader definition is more in line with some international studies (see, for instance, Beer and Schurz, 2007; Djoudad, 2010; IMF, 2011; Bankowska et al., 2015).

We contribute to the literature on microsimulation models designed to evaluate the vulnerability of households. The first papers on this topic were those of Johansson and Persson (2006), Vatne (2006), and Zajączkowski and Żochowski (2007), from Sweden, Norway and Poland, respectively. Among recent papers evaluating households' vulnerability under normal conditions and scenarios of stress there are Djoudad (2010), Michelangeli and Pietrunti (2014), as well as Ampudia et al., (2016), from Canada, Italy, and several European countries. To our knowledge, our paper is the first to develop a methodology for the projections of consumer credit and mortgage renegotiations. By integrating micro and macro data we preserve heterogeneity while exploiting the higher frequency of the macro data.

The paper is organized as follows. Section 2 provides a description of households' financial vulnerability based on the SHIW. In Section 3 the model of households' financial vulnerability is developed to include consumer credit dynamics and mortgage

[9] We provide an example in the Appendix.

renegotiations. Section 4 presents the backtest exercises and the results for the baseline scenario. Section 5 analyses all households with a DSR above 30 per cent. Section 6 concludes.

## 2. SHIW data

### 2.1. Descriptive statistics and definition of vulnerable households

Our analysis exploits the 2010-16 waves[10] of the SHIW, a biannual survey that comprises about 8,000 households distributed over about 300 Italian municipalities. In each wave of the survey, half of the sample is longitudinal and half is renewed (unbalanced panel). The dataset contains information on household demographic characteristics (age, education, family composition, etc.) as well as consumption, income, wealth, and liabilities. With respect to the latter item, households are asked to distinguish between mortgages on their first house or on other real estate, and consumer credit. Loans for household needs other than property purchase or renovation[11] represent the largest share of consumer credit (around 80 per cent) whereas bank overdrafts and credit card receivables only account for 16 and 4 per cent respectively. For loans other than bank overdrafts and credit card receivables, households declare the outstanding debt amount, the initial amount borrowed, the year when the loan was originated, its maturity, the annual installment, the interest rate paid and the rate type (adjustable or fixed rate). In 2014 and 2016, questions aimed at capturing mortgage renegotiations were also introduced.

Vulnerable households are those with a DSR above 30 per cent and income below the median of the population. Their identification accordingly implies the computation of the DSR for each household. To this end, we exploit the information provided by households on mortgage installments and on loans for needs other than property purchase or renovation. With respect to credit card receivables and bank overdrafts this information is not available; we thus assume that each year the whole credit card debt and one fifth of bank overdrafts are repaid. The assumption on the repayment of credit card debt is quite natural, since it is often repaid in a few months; the one about bank overdrafts stems from the fact that in Italy they must be repaid upon the bank's request, but usually this type of debt is not repaid for several years. We assume, therefore, that a household repays the total bank overdraft in five years. On the one hand, this is a credible amount of time if we look at the dynamics of bank overdrafts within the longitudinal component of the SHIW,

[10] We consider these waves to capture the most recent dynamics.

[11] Loans for household needs other than property purchase or renovation include loans for purchase of motor vehicles (car, motorcycle, etc.), for the purchase of furniture, appliances, etc., for non-durable goods (vacations, etc.), for other purchases or daily expenses, for education expenses (degree, master). They could be collateralized or they could be personal loans or loans for pledge of "fifth of salary".

but on the other hand it is also a conservative choice (meaning that it tends to amplify debt service ratios), since bank overdrafts might be repaid in more than five years.

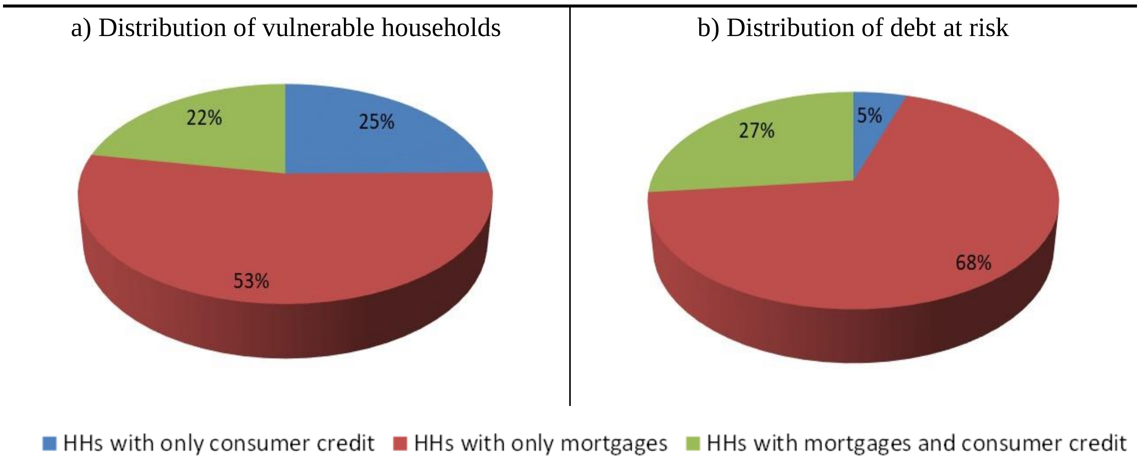
In our sample the share of vulnerable households in the period 2010-16 was around 2 per cent, peaking at 2.9 per cent in 2012, and then decreasing to 1.6 per cent in the last wave. The debt at risk was around 16 per cent in the same period, going from 19.0 per cent in 2012 to 10.4 per cent in 2016.

### 2.2. Consumer credit and vulnerability

In Italy almost 50 per cent of vulnerable households have consumer credit, often together with a mortgage (Figure 3a), and they detain over 30 per cent of total household debt (Figure 3b). The share of debt held by those with consumer credit only (without a mortgage) is, however, much lower. Indeed, the average amount of consumer credit held by vulnerable households (€10,000; Table 1) is significantly lower than that associated with mortgages (about €80,000). This suggests that the risks for financial stability due to consumer credit in isolation are limited overall, but they are not negligible if consumer credit is combined with mortgage debt.

**Figure 3**

**Financial vulnerability by type of debt**
(*averages 2010-16; percentages*)




Source: Our calculations based on SHIW data. Debt at risk refers to the share of debt held by vulnerable households.

Moreover, the higher interest rates charged on mortgages and consumer credit extended to vulnerable households likely reflect their higher riskiness with respect to the other low-income households.

**Table 1**
**Household debt**
(*averages 2010-16; euros and per cent*)

| | Consumer credit | | Mortgages | |
|---|---|---|---|---|
| | **Amount** | **Interest rate (1)** | **Amount** | **Interest rate (1)** |
| Vulnerable HHs | 10,001 | 5.0 | 80,734 | 4.3 |
| Other low-income HHs | 5,446 | 4.4 | 52,009 | 4.1 |

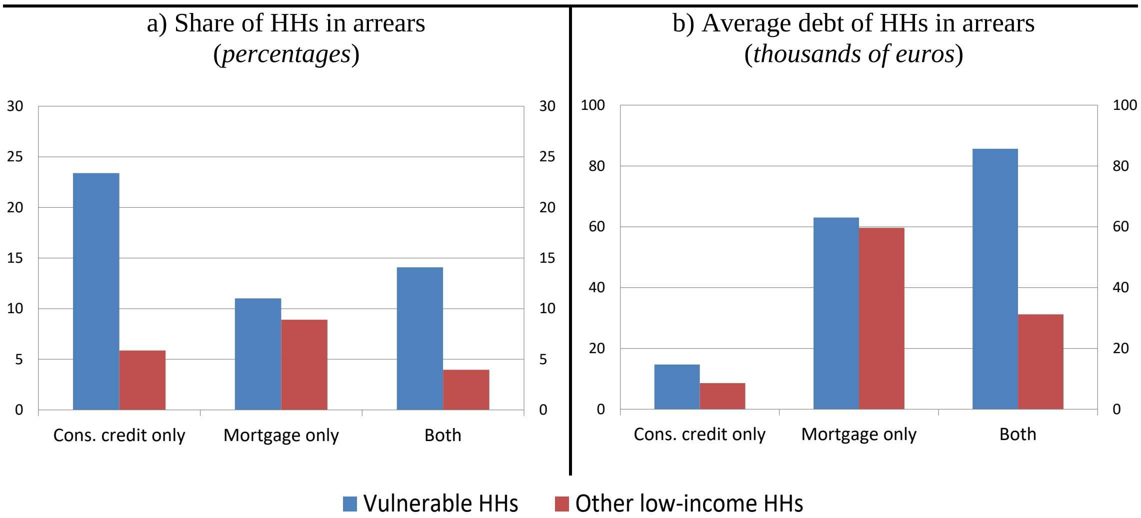
Source: Our calculations based on SHIW data.

(1) Interest rates are calculated as weighted averages of the amount borrowed. Other low-income households include households with income below the median of the population and a DSR below 30 per cent.

To assess in more detail the financial fragility of vulnerable households we look at those that declare they are in arrears by more than 90 days. Being in arrears does not necessary imply defaulting, but it is reasonable to assume that households in arrears are at higher risk of having debt sustainability problems. As expected, vulnerable households are more likely to be in arrears and, when they are, they have higher debt than other low-income but non-vulnerable households (Figure 4). More specifically, 23 per cent of vulnerable households with consumer credit only are in arrears, compared to about 6 per cent for the other low-income non-vulnerable ones. Interestingly, households tend to be in arrears more often when debt is represented by consumer loans rather than mortgages.

**Figure 4**

**Financial vulnerability and arrears of more than 90 days**
(*averages 2010-16*)

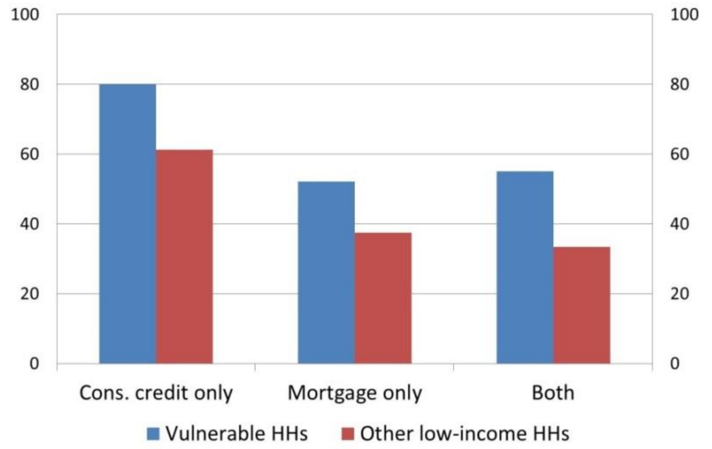



Source: Our calculations based on SHIW data. Other low-income households include households with income below the median of the population and a DSR below 30 per cent.

Another indicator of debt sustainability is households' subjective perception of economic difficulty, measured by the share of households that declare their income is not sufficient to see them through to the end of the month without difficulty. The share of households that face financial difficulties is higher among vulnerable households than among other low-income ones (Figure 5). Furthermore, the share of households facing financial difficulties is particularly pronounced among those that have only consumer credit. This suggests that consumer credit is used to finance unsustainable levels of consumption, with possible negative effects on debt sustainability.

**Figure 5**

**Subjective perceptions of economic difficulty** (1)
(*percentages; averages 2010-16*)




Source: Our calculations based on SHIW data.
(1) Share of households declaring that their income is not sufficient to see them through to the end of the month without difficulty.

## 2.3. Mortgage renegotiations and vulnerability

With interest rates at exceptionally low levels, mortgage renegotiations have likely helped to ease households' difficulties in meeting their debt repayments in recent years. However, survey data on mortgage renegotiations are limited[12] and only a few simple statistics can be reliably calculated. According to SHIW data, about 8 per cent of indebted households revised their contract terms (5 per cent in 2014, 12 per cent in 2016) and around 30 per cent of these had both mortgages and consumer credit. Households that chose to revise their mortgage terms were, on average, paying higher interest rates than other households in the previous wave; after renegotiation the rate charged was lower. About one third of these households moved from a condition of vulnerability to one of non-vulnerability.

[12] Only the 2014 and 2016 waves of SHIW report information on mortgage renegotiations.

## 3. Modelling households' vulnerability including consumer credit and mortgage renegotiations

In this section we describe how we build our projections of households' vulnerability over time. Specifically, we present the approach employed to model both consumer credit dynamics[13] and mortgage renegotiations. For the income projections we rely on the modelling approach in Michelangeli and Pietrunti (2014), which takes into account different characteristics of household groups.

With respect to consumer credit, we take a three-step approach. First, we model households' participation in the consumer credit market; second, we project households' loan amount by replicating the macro growth rate of consumer credit; finally, we compute the installments using a standard French amortization schedule. For mortgage renegotiations, we assume that households revise their contract terms if their mortgage rate is significantly above current market rates.

### 3.1. Modelling consumer credit

#### 3.1.1. Participation in the consumer credit market

For each household *i*, participation in the consumer credit market in period *t* depends on the previous period's participation in both the consumer credit market and in the real estate market, on the income quartile, and on purchases of consumer durables:

$$D_{cc}(i,t) = \alpha_0 + \alpha_1 D_{cc}(i,t-1) + \alpha_2 D_{imm}(i,t-1) + \alpha_3 D_y(i,t) +$$

$$+\alpha_4 D_{durables}(i) + \varepsilon(i,t) \text{ for } i = 1,\dots,I; \;\; t = 1,\dots,T \qquad (1)$$

where $D_{cc}(i,t)$ is a dummy variable equal to 1 if household *i* has a consumer loan in year *t*, $D_{imm}(i,t-1)$ is a dummy variable equal to 1 if household *i* has a mortgage loan in the previous period.[14] $D_y(i,t)$ is a vector of income quartile dummies. $D_{durables}(i)$ is a vector of household durable consumption dummies. We prefer using a vector of dummies for the amount of durable consumption, rather than a continuous variable, to minimize the errors associated with the projections of this variable. Accordingly, $D_{durables}(i)$ is

[13] With respect to Michelangeli and Pietrunti (2014), a broader definition of consumer credit that also includes bank overdrafts and credit card receivables is considered which, however, leads to a small increase in the debt and in the debt service ratio. This means that the share of vulnerable households increases only marginally (by fewer than 10 bps) and the amount of debt held by vulnerable households (debt at risk) remains basically unchanged (when looking at the survey data).

[14] The SHIW data are biannual, while the model projections are annual. As previous period participation is very relevant to current period participation and for our projections, we assume that a household with a consumer credit loan or a mortgage at time (*t-2*), i.e. in the previous wave, continue to have it at time (*t-1*) as well.

defined over five intervals, which were chosen starting from its sample distribution.[15] We assume that the errors are normally distributed.

The regression coefficients imply that having a consumer debt or a mortgage in the previous period is associated with a higher probability of participating in the consumer credit market in the current period (Table A.2). Furthermore, households with higher income and belonging to higher classes of durable consumption are more likely to have a consumer loan.

The coefficients for each regressor $(\widehat{\alpha_0}, \dots, \widehat{\alpha_4})$, as well as the mean $\hat{\mu}$ and the standard deviation $\hat{\sigma}$ of the error term, are then used to simulate each household's participation in the consumer credit market. We run 50 different simulations to have some variability in the estimated error term.[16]

The estimated probability of entering the consumer credit market for each household is given by:

$$\widehat{D_{cc}}(i,t) = \widehat{\alpha_0} + \widehat{\alpha_1} D_{cc}(i,t-1) + \widehat{\alpha_2} D_{imm}(i,t-1) + \widehat{\alpha_3}\widehat{D_y}(i,t) + $$

$$+\widehat{\alpha_4} D_{durables}(i) + \hat{\varepsilon}(i,t) \text{ for } i = 1, \dots, I, \mathrm{t} = 1, \dots, \mathrm{T} \qquad (2)$$

For each household and for each period we obtain a value $\widehat{D_{cc}}(i,t)$ that captures the probability of participating in the consumer credit market. However, in our microsimulation model we are not interested in a continuous probability, but in identifying which households participate in the consumer credit market and which households don't. In other words, we need a variable equal to 1 for participants and equal to 0 for non-participants. Thus, for each year, we ordinate the values $\widehat{D_{cc}}(i,t)$ and we compute the threshold $\widehat{D^{Threshold}_{cc}}(\iota,t)$, which allows us to capture recent trends in participation.[17]

The simulated value of participation in the consumer credit market for household *i* is:

$$D_{cc}^{simul}(i,t) = \begin{cases} 1 \text{ if } \widehat{D_{cc}(\iota,t)} > \widehat{D^{Threshold}_{cc}}(\iota,t) \\ 0 \text{ if } \widehat{D_{cc}(\iota,t)} \leq \widehat{D^{Threshold}_{cc}}(\iota,t) \end{cases} \text{ for } i = 1,..,I;\ \ t = 1,..,T \qquad (3)$$

[15] The intervals are 0; (0; €500]; (500; €1,500]; (1,500; €5,000]; 5,000+. The 25th, 50th, 75th percentiles of the distribution are equal to about €500, €1,500, and €5,000 respectively.

[16] Over the period 2010-16, the error is distributed as $\varepsilon(\mathrm{i},\mathrm{t}) \sim \mathrm{N}(0,0.31)$. Increasing the number of simulations has minor effects on the final results.

[17] Given the empirical evidence based on the last two surveys, according to which the share of households with consumer credit was about constant and equal to 13 per cent (while the amount of consumer credit varied significantly across the two waves), we set the threshold $\widehat{\mathrm{D}^{Threshold}_{cc}}(\iota,t+x)$ at the 87th percentile of the distribution, assuming a constant participation also in the near future. Robustness checks indicate that small variations in this assumption would not significantly alter our final results.

### 3.1.2. Projection of consumer loan amount

After having determined whether a household participates in the consumer credit market, we need to assign a value for the consumer loan amount. We assume that changes in consumer credit depend on a household's income quartile, household consumption of durables, and the aggregate dynamics of consumer credit.

Therefore, for each household *i* that already participated in the consumer credit market in the previous period, we compute the change in the consumer credit amount

$$\Delta L_{cc}(i,t) = L_{cc}(i,t) - L_{cc}(i,t-1)$$

and then we run the following regression:

$$\Delta L_{cc}(i,t) = \alpha_1 tc_{cc}(t) + \alpha_2 D_y(i,t) + \alpha_3 D_{durables}(i) \quad for\ i = 1,..,I;\ \ t = 1,..,T \tag{4}$$

where $tc_{cc}(t)$ is the growth rate of consumer loans to households in the Italian economy. The results of equation (4) are reported in Table (A.3) in the Appendix. As expected, $\alpha_1$ has a positive sign reflecting the fact that stronger aggregate credit growth translates into higher average household consumer credit. Households with higher consumer durable expenses, especially those belonging to the fifth class, tend to report larger positive changes in consumer credit, suggesting that high durable expenses tend to be persistent over time. Nevertheless, those households mostly belong to the upper income quartiles and thus a smaller coefficient for them slightly reduces the overall impact.

For each household *i* already participating in the consumer credit market, the estimated change in consumer credit at time *t* is computed using the coefficient of the regression (4):

$$\Delta \widehat{L_{cc}(\iota},t) = \widehat{\alpha_0} + \widehat{\alpha_1} tc_{cc}(t) + \widehat{\alpha_2}\widehat{D_y}(i,t) + \widehat{\alpha_2} D_{\widehat{durables}}(i,t)$$

$$for\ i = 1,..,I;\ \ t = 1,..,T \tag{5}$$

The projection of the consumer loan amount is given by the previous period loan amount plus the estimated change:[18]

$$L_{cc}^{simul}(i,\ t) = L_{cc}(i,t) +\ \Delta \widehat{L_{cc}(\iota},t) \qquad for\ t = 1$$

$$L_{cc}^{simul}(i,t) =\ L_{cc}^{simul}(i,t) +\ \Delta \widehat{L_{cc}(\iota},t)\ \ for\ \ t > 1 \quad and\ \ i = 1,..,I \tag{6}$$

For households that are estimated to participate in the consumer credit market at time (*t+1*) for the first time, we do not have the previous period's consumer credit, thus we estimate the loan amount by the means of a pseudo panel. First, we create *G* groups of similar households on the basis of their age class, job type, durable consumption class,

[18] Note: for the first year of the simulation ($t = 0$ ; $x = 1$ ) we have actual data on $L_{cc}(i,t)$ from the survey; for the following year $L_{cc}(i,t+x-1)$ we have the results from the model.

and mortgage tenure. Second, we estimate equation (4) for the median group change in the consumer loan amount, $\Delta L_{cc}(g, t)$. Third, a household *i*, that belongs to group $g$ and enters the consumer credit market at time *t+x*, is assigned the loan amount estimated on the pseudo panel regression:

$$L_{cc}^{\widehat{simul}(\iota,g,t)} = L_{cc}(g,t) + \Delta\widehat{L(g,t)} \qquad for\ t = 1$$

$$L_{cc}^{simul}\widehat{(\iota,g,}t+x) = L_{cc}(g,\widehat{t+x}-1) + \Delta L_{cc}\widehat{(g,t}+x) \qquad for\ \ t > 1$$

$$and\ \ i = 1,..,I;\ \ g = 1,...,G \qquad (7)$$

After computing the loan amount for each household that participates in the consumer credit market, we construct the total consumer debt in the simulated economy:

$$TL_{cc}^{simul}(t) = \sum_{i=1}^{I} L_{cc}^{\widehat{simul}(\iota},t) \qquad for\ t = 1,...,T\ and\ \ i = 1,..,I \quad (8)$$

Then, we calculate the growth rate of the consumer credit loan in our simulation and we compare it with the actual aggregated data. As our goal is to have similar growth rates, we introduce a multiplicative adjustment factor $adj(t)$ for each household loan amount, which then becomes equal to $adj(t)L_{cc}^{\widehat{simul}(}\iota,t)$. It is comforting to observe that the adjustment factor turns out to be quite small.[19]

### 3.1.3. Annuitization of consumer loans

Once we have the projected consumer debt we can perform annuitization to get (annual) installments. Assuming that consumer debt is repaid according to a French amortization schedule, we need to make assumptions on maturity and interest rates.

For households that already have consumer debt in the survey data, we assume that the maturity and interest rate of the overall consumer debt are the weighted averages of those of their components (loans for household needs other than property purchase or renovation, credit card receivables, and bank overdrafts).

The theoretical debt that would be consistent with the observed installments, under the assumptions just mentioned (remember that in *t=0* we observe both installments and debt), is very close to the actual declared debt (Figure 6).

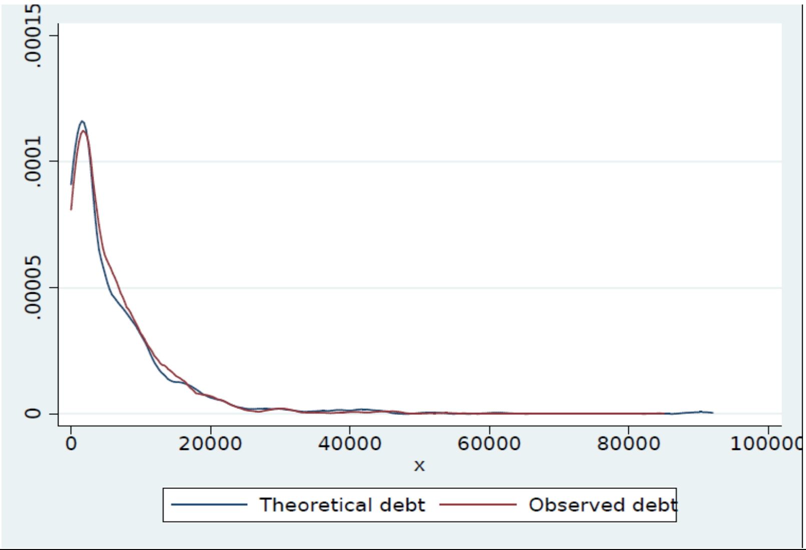
Depending on whether the change in consumer credit ($\Delta L_{cc}(i,t)$) is negative or positive we have two different approaches. In the first case, $\Delta L_{cc}(i,t) < 0$, we assume (partial) reimbursement of the outstanding debt. In the second case, $\Delta L_{cc} > 0$, we assume that a new contract of consumer credit is signed, and its installments are added to those of the old (already outstanding) debt. The new loan has the same maturity as the old one

[19] The adjustment factor is quite small overall. For example, in the 2016-18 simulation, it equals 1.08 for the first year and 1.09 for the second year.

at origination and the same type of interest rate (fixed vs. variable). We assume therefore that the household's preferences for maturity and type of interest rate remain constant over time.

**Figure 6**

**Distribution of theoretical and observed debt** (1)




Source: Our calculations based on SHIW data.
(1) Observed debt refers to the actual SHIW outstanding debt for each household. Theoretical debt refers to the amount of debt that would be consistent with the installments paid by each household.

For those that do not already have consumer debt at *t=0*, but are projected to participate in the consumer credit market in the following years, we assume that they choose variable interest rates,[20] sign their contract at the current rate, and, based on the observed data, set debt maturity at 5 years.

### 3.2. Modelling mortgage dynamics with renegotiations

With respect to modelling mortgage dynamics, we extend Michelangeli and Pietrunti's model (2014), according to which households with an existing mortgage repay their debt according to a French amortization schedule, while new mortgage originations are modelled to mirror the average characteristics of households that have become indebted in the recent past. Given the empirical evidence on the volume of mortgage renegotiations based on supervisory reports data, we introduce to this framework the possibility for households to revise their contract terms.

[20] As we are evaluating the risks stemming from the household sector, we make assumptions to capture the more volatile scenario. However, alternative approaches, such as assuming that the share of new contracts at adjustable rates remains constant over time, would not significantly change our results due to the low average debt related to consumer credit.

Since, in the SHIW only a few households declare that they have renegotiated their debt, we cannot develop an extension of the model that exploits households' characteristics. Accordingly, our novel modelling approach relies on a few assumptions that are necessary to capture the heterogeneity of mortgage renegotiations. We assume that mortgage renegotiation occurs when households pay a mortgage rate, which is at least 3 percentage points higher than the reference rate plus a household's specific spread. After renegotiation, the bank sets a rate equal to the current reference rate plus the household's spread.

More specifically, for indebted households we calculate the mortgage spread, $Spread(i)$, starting from the standard relation according to which a household's mortgage rate $r_m(i,t)$[21] equals the reference rate $r_{ref}(i)$[22] plus a spread.

$$Spread(i) = r_m(i,t) - r_{ref}(i) \ \ for\ i = 1,..,I; \ \ t = 1,..,T \tag{9}$$

For fixed-rate mortgages, the spread is calculated as the difference between the mortgage rate declared to be paid at time *t* and the 10-year IRS at origination; for variable-rate mortgages, the spread is given by the difference between the declared rate in year *t* and the 3-month Euribor in the same year. The spread reflects the differences in households' riskiness and is highly heterogeneous across households. Regression coefficients imply that the spread is higher for households with low education, for those living in the South, and for those that are self-employed or not working (Table A.4). When the household's spread turns out to be negative, likely due to mistakes in answering the survey's questions, we assign the median spread of the group of households with similar characteristics (education, geographic area, and occupation).

We assume that at time *t* a household renegotiates its debt if its mortgage rate[23] exceeds the sum of the current period reference rate $r_{ref}(t)$,[24] its specific spread, and a parameter α:

$$r_m(i,t) > r_{ref}(t) + Spread(i) + \alpha \quad for\ i = 1,..,I; \ \ t = 1,..,T \tag{10}$$

α is set to be equal to 3 percentage points.[25] This parameter's value was selected as it allows us to obtain model statistics on the share of households that renegotiate their

[21] To compute the spread, we exploit the SHIW information on the mortgage rate declared to be paid by household *i* at time *t*, $r_m(i,t)$.
[22] The reference rate $r_{ref}(i)$ is specific to each household as it depends on the characteristics (year of origination and rate type) of its loan.
[23] In the years of the simulation, the household's mortgage rate is exactly equal to the one declared in the last wave (for fixed-rate mortgages) or it is adjusted to reflect variations in the Euribor (for variable- rate mortgages).
[24] The current period reference rate $r_{ref}(t)$ is the 10-year IRS for fixed-rate mortgages and the 3-month Euribor for variable-rate mortgages.
[25] Small modifications on the parameter α have minor effects on the final results.

mortgage terms (Panel A of Table 2) and on the share of debt that they hold (Panel B of Table 2) quite close to those based on the SHIW data.

**Table 2**

**Mortgage renegotiations**
(*percentages*)

| | SHIW | MODEL[(1)] |
|---|---|---|
| Panel A. Share of households that renegotiate their mortgage terms among indebted households | | |
| 2014 | 5.0 | 5.4 |
| 2016 | 11.7 | 12.6 |
| Panel B. Share of debt held by households that renegotiate their mortgage terms | | |
| 2014 | 4.0 | 2.8 |
| 2016 | 14.9 | 12.0 |

(1) Averages over two years.

We assume that banks do not modify the spread applied to each household, i.e. if a household was considered risky when the mortgage was initially granted, the household would continue to be so and the bank would charge the same spread.[26] Upon renegotiation, the new mortgage rate paid by the household $r_{m,REN}(i,t)$ equals the current period reference rate plus the household's spread:

$$r_{m,REN}(i,t) = r_{ref}(t) + Spread(i) \qquad for\ i = 1,..,I\ and\ \ t = 1,..,T \qquad (11)$$

## 4. Model results

In this section, we present the results obtained by simulating the model under different specifications. We define as 'old' the model described in Michelangeli and Pietrunti (2014), and as 'new' the model augmented with both mortgage renegotiations and consumer credit dynamics. Macroeconomic inputs of the model are described in the Appendix.

### 4.1. Backtesting

To evaluate the model's performance in terms of the accuracy of its projections, we carry out backtest exercises on two waves of the SHIW. Starting from either the 2012 or the 2014 wave, we present the two-year out-of-sample predictions of the share of vulnerable households in the population and the share of total debt held by them (Figure 7).

[26] Given the limited size of the phenomenon in the data, this is the best possible assumption that allows us to maintain the heterogeneity in the spread.

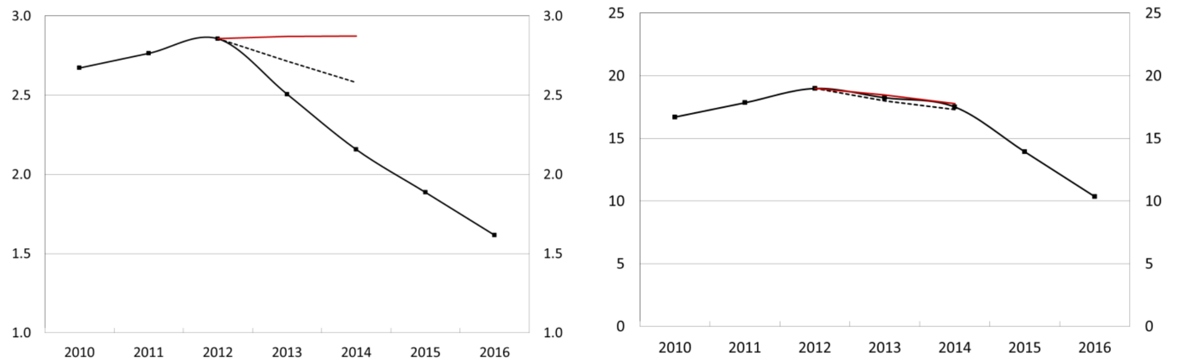
**Figure 7**

**Backtest exercises - Vulnerability**

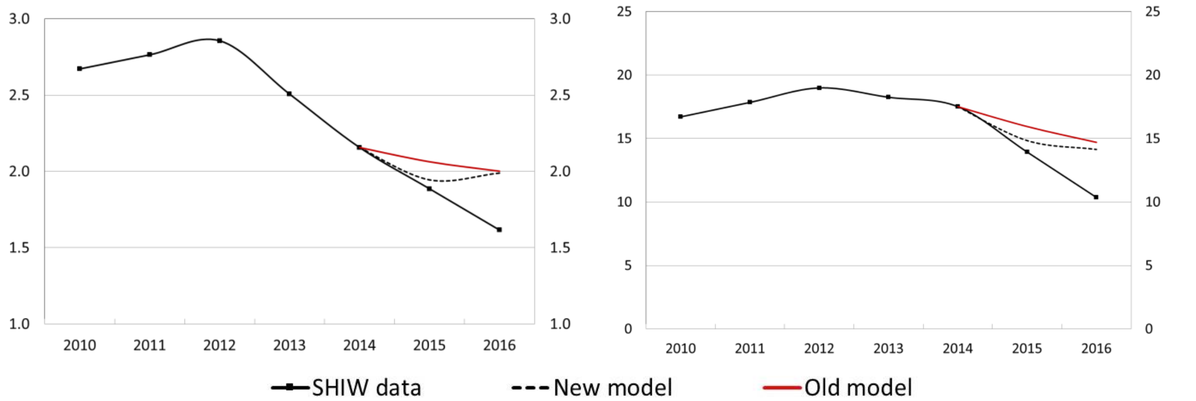
(*percentages*)

a) Share of vulnerable households b) Debt at risk (1)

**2012-14**




**2014-16**




(1) Debt at risk refers to the share of debt held by vulnerable households. The black line with diamonds represents actual SHIW data; the red and the dotted lines represent the out-of-sample projections for the 'old' and 'new' models respectively. These projections correspond to the median values across 50 simulations for the two model specifications.

For the period 2012-14, characterized by positive economic growth, the low interest rates and the contraction in consumer credit contribute to the reduction in the share of vulnerable households. By contrast, with respect to the debt at risk, the differences between the two models are negligible, reflecting the fact that a contraction in the share of vulnerable households with consumer credit has a limited impact on the total debt at risk. For the period 2014-16, in a context of very low interest rates, accounting for the possibility of revising the contract terms through renegotiations is crucial for a better prediction of both indicators of vulnerability. Consumer credit growth, mostly concentrated among richer households, also helps to reduce the vulnerabilities of low-income ones.

Overall, both backtesting exercises show that the new model has superior out-of-sample predictions and is better equipped to capture the downward trend of vulnerability observed in recent years.

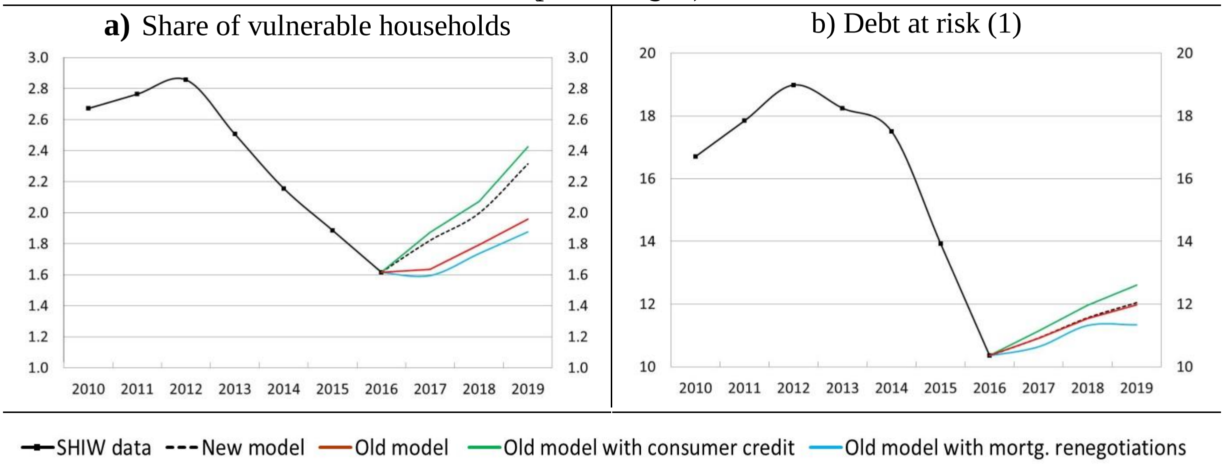
### 4.2. Baseline simulation over the period 2016-19

Figure 8 shows the prediction of the share of vulnerable households (Panel a) and the share of total debt held by these households (Panel b) in 2019, starting from 2016, the last SHIW wave. According to all model specifications, household vulnerability is projected to increase. The new model indicates that between 2016 and 2019 the percentage of vulnerable households would increase from 1.6 to 2.3 per cent, while the share of debt at risk would change only slightly, from 10.4 to 12.0 per cent.[27]

In the first year of the simulation the projections of the old model indicate that the share of vulnerable households would remain about stable as the increase in income growth, coupled with low interest rates, would be sufficient to compensate for the effects of the increase in the growth rate of mortgages. The new model, instead, projects an increase in the share of vulnerable households, which is entirely driven by the high growth rate of consumer credit. In the second year of the simulation a rise in the interest rate, which affects both the loan payments of households holding a variable interest rate mortgage and those associated with new originations, and positive credit growth (for both mortgages and consumer credit), help push up the share of vulnerable households despite positive income growth. The total effect is more pronounced in the new model, when consumer credit growth is also considered. In the last year of the simulation, 2019, higher interest rates and consumer credit growth would drive a further increase in the percentage of vulnerable households.

**Figure 8**

**Vulnerability in the period 2016-19**
(*percentages*)




(1) Debt at risk refers to the share of debt held by vulnerable households.

[27] Confidence intervals based on 50 simulations are reported in Figure A.2 in the Appendix.

In terms of debt at risk, the differences between the old and new models are negligible, since the negative effects on vulnerability associated with the expansion of consumer credit are compensated by the positive effects associated with mortgage renegotiations.

## 5. Extension of the analysis to all households with DSR above 30 per cent

So far, we have focused on households with a DSR above 30 per cent and income below the median of the population. This choice is due to the fact that highly indebted low-income households are the most fragile and display the highest default risks. However, in line with other studies in the related literature (Djoudad R., 2010, among others), a thorough assessment of financial stability risks stemming from households' debt also requires monitoring highly indebted households with high income.

We therefore analyze the risks related to households with a DSR above 30 per cent and income above the median of the population. As shown in Table 3, even though this group of households represents a small share of the population, it holds about 20 per cent of total household debt.

**Table 3**

**Distribution of households by income and DSR**
(*percentages; averages over the period 2010-16*)

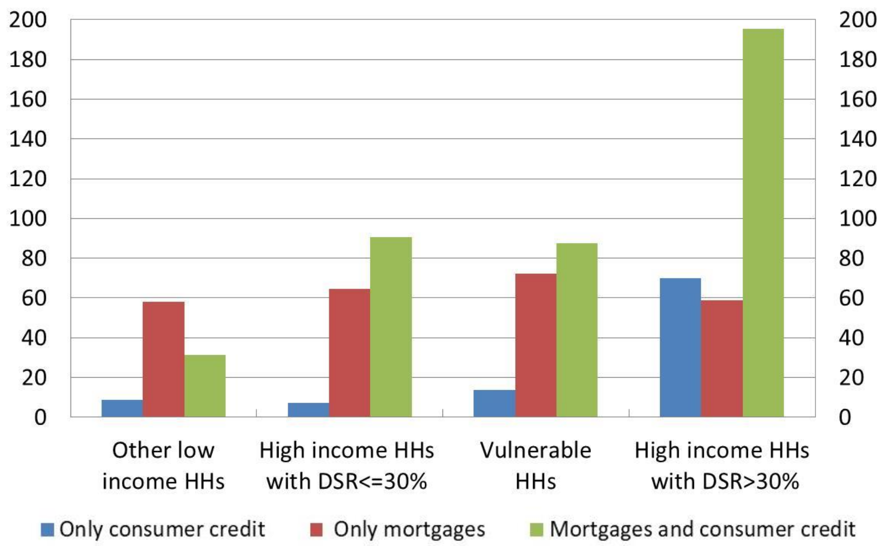
| | Share of households | Share of debt |
|---|---|---|
| Vulnerable HHs | 2.3 | 15.8 |
| Other low-income HHs | 47.7 | 13.9 |
| | | |
| High-income HHs with DSR>30% | 1.5 | 18.3 |
| High-income HHs with DSR≤30% | 48.5 | 52.0 |

Source: Our calculations based on SHIW data. High-income households are those with income above the median of the population.

The importance of this group for financial stability analysis is seen by the probability of being in arrears by more than 90 days, which is about 4.1 per cent, whereas it is only 1.4 per cent for high-income low-DSR households. Moreover, the former group of households in arrears is considerably more indebted than all other groups (Figure 9).

**Figure 9**

**Average amount of debt among households in arrears**
(*thousands of euros; averages over 2010-16*)




Source: Our calculations based on SHIW data. High-income households are those with income above the median of the population.

High- and low-income households with a DSR above 30 per cent are similar with respect to their ratio of liquid financial assets (deposits, certificates of deposits, repos, postal accounts) to loan installments (liquidity index; Table 4), which measures the number of years during which a household could service total debt only with the most liquid financial assets. Both groups of households have low liquidity relative to the amount of their installments (liquidity index). Thus, all households with a DSR above 30 per cent emerge as particularly fragile since they can cover their debt installments for less than one year with their most liquid assets.

**Table 4**

**Wealth indicators for indebted households**
(*euros; averages over the period 2010-16*)

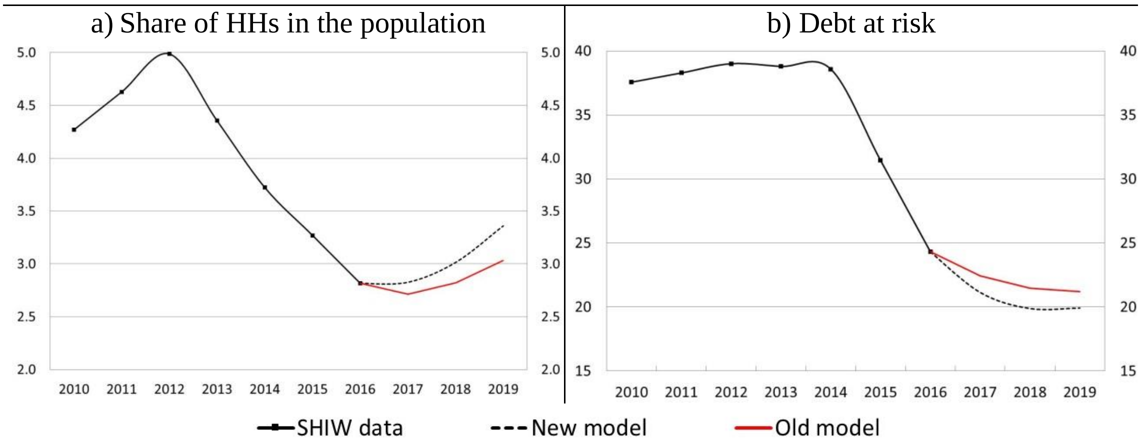
| | Total wealth | Financial wealth | Liquid assets | Liquidity index (fa/installment) |
|---|---|---|---|---|
| Vulnerable HHs | 116,728 | 4,604 | 3,405 | 0.62 |
| Other low-income HHs with DSR<30% | 100,238 | 5,950 | 4,654 | 6.50 |
| High-income HHs with DSR>30% | 348,463 | 26,905 | 13,427 | 0.82 |
| High-income HHs with DSR≤30% | 335,674 | 36,104 | 16,190 | 15.5 |

Source: Our calculations based on SHIW data. *fa* indicates liquid financial assets. High-income households are those with income above the median of the population.

Figure 10 shows the baseline projections for the period 2016-19.[28] With this broader definition, the share of vulnerable households in the population in 2016 is about 1 percentage point higher (2.8 per cent) and the share of debt at risk is about 14 percentage points higher (24.3 per cent) than in the case where only households with a DSR above 30 per cent and income below the median are considered. According to the new model, the share of vulnerable households is projected to increase to 3.4 per cent in 2019, in response to significant consumer credit growth. The share of debt held by all vulnerable households instead is projected to move from 24.3 to 19.9 per cent between 2016 and 2019. In this case the reduction would be greater than that estimated for low-income vulnerable households only. This is due to the fact that the effect of mortgage renegotiations is greater for high-income highly-indebted households.

**Figure 10**

**All households with a DSR>30 per cent in the period 2016-19**
(*percentages*)




*Note*: Debt at risk refers to the share of debt held by households with DSR above 30 per cent.

## 6. Conclusion

This paper presents a novel modelling approach for the evolution of consumer credit and mortgage renegotiations within a microsimulation model of households' vulnerability. In particular, we extend Michelangeli and Pietrunti's model (2014) to account for the recent increase in consumer credit and its progressive concentration among high-income households, and to account for the wide recourse to mortgage renegotiations in a context of very low interest rates.

These new features of the microsimulation model have proved crucial for carefully assessing the financial stability risks stemming from the household sector. The model with consumer credit and mortgage renegotiations overperforms Michelangeli and Pietrunti (2014) in capturing the trends in vulnerability over the last few years.

[28] The backtest exercises show that the model closely replicates the dynamics observed even applying this broader definition of vulnerability (Figure A.3 in the Appendix).

Both mortgage renegotiations and consumer credit affect vulnerability, though in opposite ways. By reducing loan installments, mortgage renegotiations help to decrease vulnerability. Consumer credit drives, instead, an increase in the share of vulnerable households, though with limited effects on the overall debt at risk. A model accounting separately for these two forces can come in particularly handy, especially when they impact on household financial vulnerability in opposite directions and it is not possible to establish the overall effect ex ante.

The model is also suitable for analyzing the dynamics of vulnerability for all households with a DSR above 30 per cent. Moreover, it is useful to evaluate scenarios of stress relative to the interest rates of both mortgages and consumer credit (an example is presented in the Appendix). It could also be used to assess specific policies on household debt to evaluate their impact on the solvency of households.

## 7. References


Ampudia, Miguel, Has van Vlokhoven, and Dawid Żochowski (2016). 'Financial fragility of euro area households.' *Journal of Financial Stability* 27: 250-262.

Bank of Italy (2018). *Financial Stability Report*, 2.

Bankowska, Katarzyna, Pierre Lamarche, Guillaume Osier, and Sébastien Pérez-Duarte (2015). 'Measuring household debt vulnerability in the euro area: Evidence from the Eurosystem Household Finances and Consumption Survey.' In: *Indicators to support monetary and financial stability analysis: data sources and statistical methodologies*, Volume 39 of IFC Bulletin, Irving Fisher Committee on Central Bank Statistics: Bank for International Settlements.

Beer, Christian, and Martin Schurz (2007). 'Characteristics of Household Debt in Austria: Does Household Debt Pose a Threat to Financial Stability?,' *Monetary Policy and the Economy*, 2nd Quarter: 58–79.

Djoudad, R (2010). 'The Bank of Canada's analytic framework for assessing the vulnerability of the household sector.' Financial System Review, 57-62.

Iacoviello, Matteo (2008). 'Household Debt and Income Inequality, 1963-2003.' *Journal of Money, Credit and Banking*, Blackwell Publishing, 40(5), 929-965, August.

IMF (2011). 'United Kingdom: vulnerabilities of private sector balance sheets and risks to the financial sector technical notes.' *IMF Country Report*, No. 11/229, July 2011.

Johansson, Martin, Mattias Persson (2006). 'Swedish households' indebtedness and ability to pay: a household level study.' *Sveriges Riksbank Econ. Rev*., 3, 24-40.

Magri, Silvia, Valentina Michelangeli, Sabrina Pastorelli, and Raffaella Pico (2019): "The expansion of consumer credit in Italy and in the euro area: what are the drivers and the risks?" Banca d'Italia, Questioni di Economia e Finanza (Occasional Papers), forthcoming.

Michelangeli, Valentina, Mario Pietrunti (2014). 'A microsimulation model to evaluate Italian households' financial vulnerability.' *International Journal of Microsimulation*, 7(3), 53-79.

Vatne, Bjørn Helge (2006). 'How large are the financial margins of Norwegian households? An analysis of micro data for the period 1987-2004?' *Norges Bank Eco. B*, LXXVII (4), 173-180.

Zajączkowski, Slawomir, and Dawid Żochowski. (2007). 'The distribution and dispersion of debt burden ratios among households in Poland and its implications for financial stability.' Proceedings of the IFC Conference on 'Measuring the financial position of the household sector', 30–31 August 2006, Basel, 62-74.

## 8. Appendix

**Table A.1**
**Loans to households**
(*millions of euros and per cent*)

| | Mortgages | | Consumer credit | | Total loans | | Percentage composition | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total (A) | Non-performing (B) | Total (C) | Non-performing (D) | Total (E) | Non-performing (F) | A/E | B/F | C/E | D/F |
| 2010 | 329,950 | 13,938 | 118,779 | 10,766 | 543,902 | 38,765 | 60.7 | 36.0 | 21.8 | 27.8 |
| 2011 | 345,406 | 16,055 | 118,476 | 11,792 | 565,345 | 46,760 | 61.1 | 34.3 | 21.0 | 25.2 |
| 2012 | 345,255 | 18,845 | 116,142 | 12,140 | 562,102 | 52,173 | 61.4 | 36.1 | 20.7 | 23.3 |
| 2013 | 341,952 | 21,728 | 111,937 | 12,088 | 554,170 | 57,161 | 61.7 | 38.0 | 20.2 | 21.1 |
| 2014 | 341,221 | 23,660 | 108,644 | 10,879 | 549,522 | 59,087 | 62.1 | 40.0 | 19.8 | 18.4 |
| 2015 | 342,698 | 25,530 | 109,993 | 9,632 | 551,824 | 60,922 | 62.1 | 41.9 | 19.9 | 15.8 |
| 2016 | 348,643 | 25,812 | 113,302 | 7,804 | 558,341 | 57,592 | 62.4 | 44.8 | 20.3 | 13.6 |
| 2017 | 355,906 | 23,588 | 121,992 | 7,035 | 567,262 | 49,521 | 62.7 | 47.6 | 21.5 | 14.2 |
| 2018-Q3 | 356,792 | 20,295 | 129,257 | 6,618 | 571,742 | 40,233 | 62.4 | 50.4 | 22.6 | 16.4 |

Source: Supervisory reports.

**Table A.2**
**OLS regression**

| | $D_{cc}$ (i,t) |
|---|---|
| $D_{cc}$(i, t-2) | 0.328** |
| | (0) |
| $D_{imm}$(i, t-2) | 0.086*** |
| | (4.12e-09) |
| Income quartile 2 | 0.027*** |
| | (0.00319) |
| Income quartile 3 | 0.037*** |
| | (0.000154) |
| Income quartile 4 | 0.041*** |
| | (0.000128) |
| Durable consumption class 2 | 0.044*** |
| | (0.000649) |
| Durable consumption class 3 | 0.055*** |
| | (2.91e-05) |
| Durable consumption class 4 | 0.081*** |
| | (1.14e-05) |
| Durable consumption class 5 | 0.212*** |
| | (0) |
| Constant | 0.023*** |
| | (1.34e-05) |
| Observations | 17,368 |
| R-squared | 0.182 |

Robust p-values in parentheses
***p<0.1, **p<0.05, *p<0.01

**Table A.3**
**OLS regression**

| | $\Delta L_{cc}(i,t)$ |
|---|---|
| $tc_{cc}(t)$ | 452.014** |
| | (180.708) |
| Income quartile 1 | -54.722 |
| | (73.468) |
| Income quartile 2 | -79.546 |
| | (71.415) |
| Income quartile 3 | -78.194 |
| | (69.991) |
| Income quartile 4 | -110.160* |
| | (66.533) |
| Durable consumption class 1 | -56.990 |
| | (67.718) |
| Durable consumption class 2 | -52.810 |
| | (82.902) |
| Durable consumption class 3 | -84.604 |
| | (81.063) |
| Durable consumption class 4 | 0.000 |
| | (0.000) |
| Durable consumption class 5 | 1,204.870*** |
| | (89.966) |
| Observations | 17368 |
| R-squared | 0.021 |

Standard errors in parentheses
***p<0.01, **p<0.005, *p<0.1

**Table A.4**
**OLS regression**

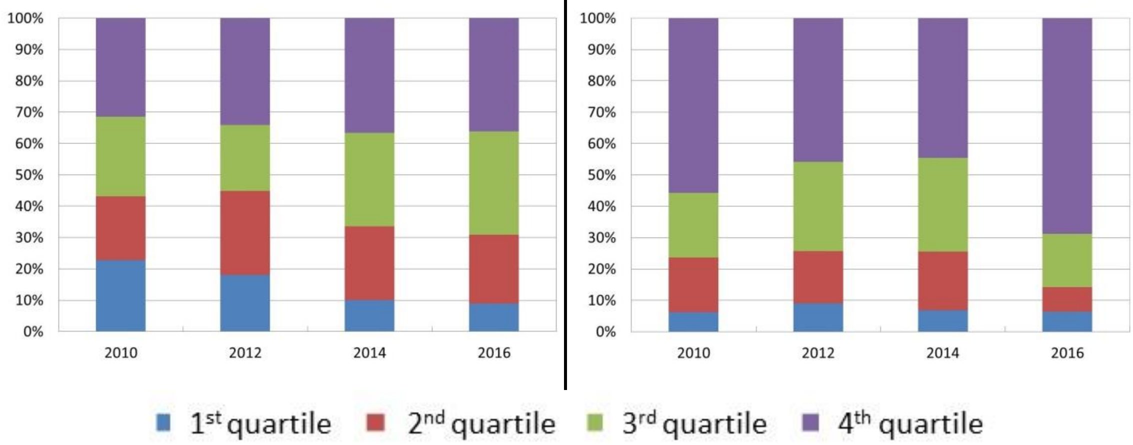
| | **Spread** |
|---|---|
| Primary school certificate | 2.067** |
| | (0.627) |
| Lower secondary school certificate | 1.518*** |
| | (0.613) |
| Upper secondary school | 1.326** |
| | (0.614) |
| University degree | 1.069* |
| | (0.619) |
| Postgraduate qualification | 0.903 |
| | (0.671) |
| Center | 0.159 |
| | (0.101) |
| South | 0.806*** |
| | (0.104) |
| Self-employed | 0.241** |
| | (0.116) |
| Not working | 0.269** |
| | (0.126) |
| Constant | -0.738 |
| Observations | 2,593 |
| R-squared | 0.048 |

Standard errors in parentheses
***p<0.1, **p<0.05, *p<0.01

**Figure A.1**

**Household debt by income groups**

a) Consumer credit | b) Mortgages



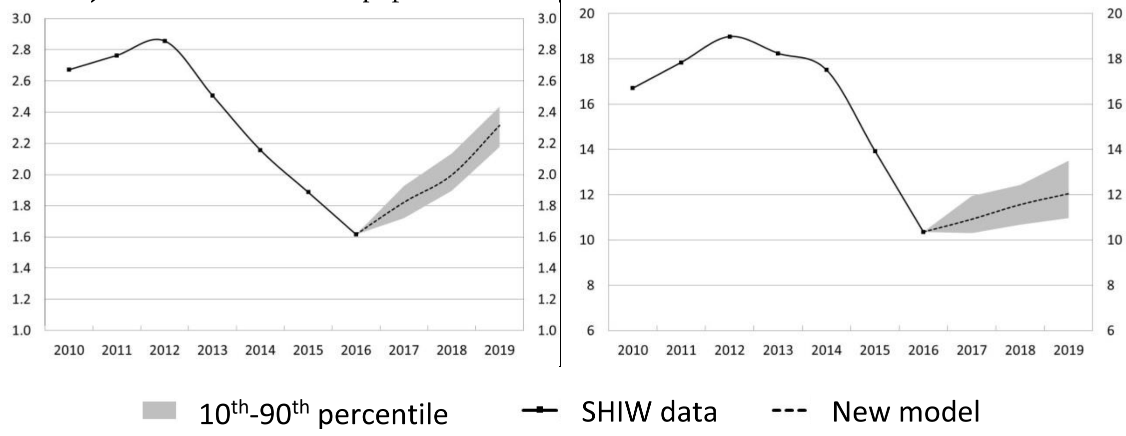

Source: Our calculations based on SHIW data.

**Figure A.2**

**Confidence intervals - vulnerability in the period 2016-19**

*(percentages)*

**a)** Share of HHs in the population | b) Debt at risk (1)




(1) Debt at risk refers to the share of debt held by vulnerable households.

**Figure A.3**

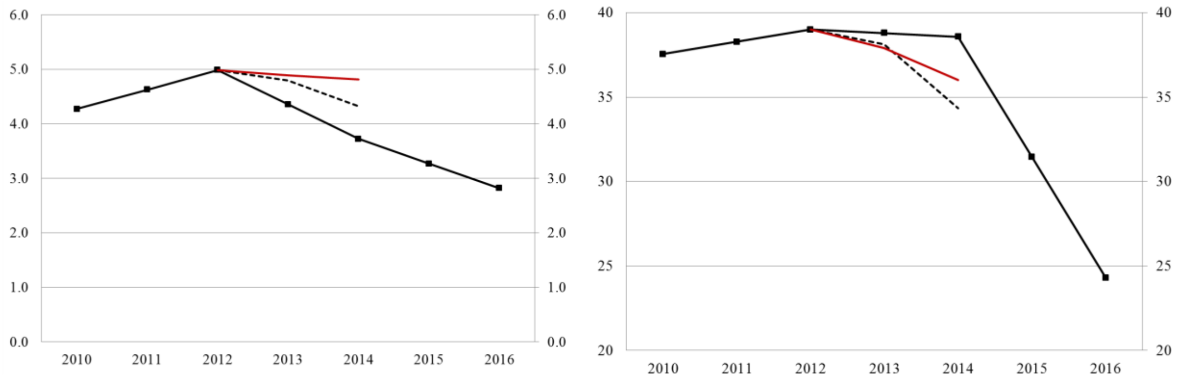
**Backtest excercises - All households with a DSR>30 per cent**

(*percentages*)

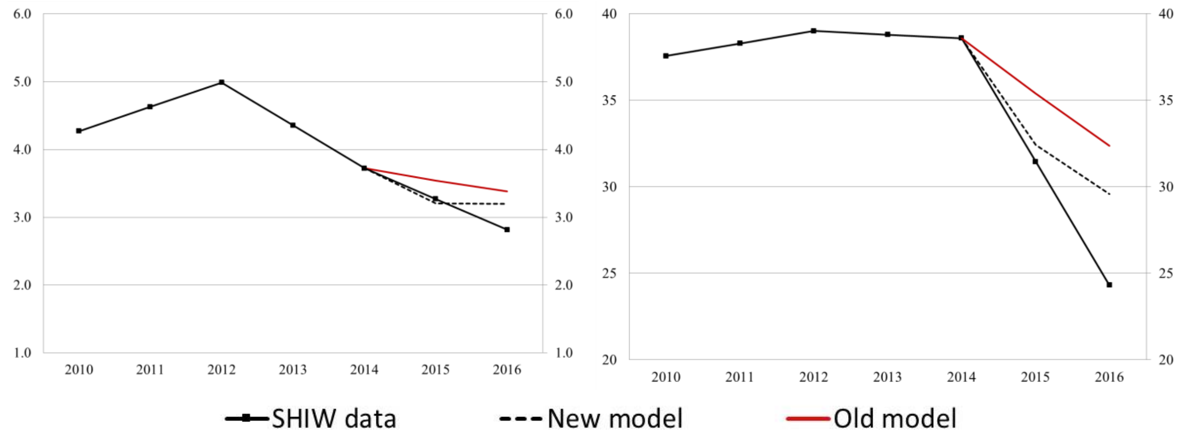
a) Share of vulnerable households

b) Debt at risk (1)

**2012-14**



**2014-16**




(1) Debt at risk refers to the share of debt held by households with a DSR above 30 per cent.

### Macroeconomic inputs

In this section we describe the macroeconomic inputs used to update the microeconomic data in our microsimulation model.[29]

First, for the projection of household income we use the growth rate of income of consumer households based on the national accounts (*Contabilità nazionale*, *CN*).

Second, for household mortgage debt and consumer credit dynamics we rely on the data on lending volumes to households for house purchase and for consumer credit. The forecasted data, which are based on a macro-econometric model developed at the Bank of Italy for internal purposes, indicate growth in household loans in 2018-19, which is particularly strong for consumer loans.

Finally, for mortgage installments we exploit the data on interest rates. Specifically, we make use of the historical data on the 3-month Euribor and the projections obtained from future contracts to assign a value at the rate of adjustable-rate mortgages. For the projection of the installments for households with a fixed-rate mortgage after renegotiation, we use the 10-year IRS and the projected average rate on mortgages to households longer than 1 year; this latter rate is based on the macro-econometric model developed at the Bank of Italy.

**Table A.5**
**Macroeconomic inputs**

| | Growth rate of income | Growth rate of mortgages | Growth rate of consumer credit | Annual change in 3-month Euribor | Annual change in 10-year IRS | Growth rate of durable consumption |
|---|---|---|---|---|---|---|
| | (%) | (%) | (%) | (basis points) | (basis points) | (%) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 2013 | 0.51 | -1.22 | -1.88 | 0.08 | -0.06 | -4.62 |
| 2014 | 0.74 | -0.80 | -0.85 | -0.19 | -0.45 | 6.39 |
| 2015 | 1.49 | 0.41 | 4.59 | -0.21 | -0.57 | 8.23 |
| 2016 | 1.47 | 1.79 | 8.25 | -0.19 | -0.35 | 5.01 |
| 2017 | 1.66 | 2.26 | 9.06 | -0.012 | 0.30 | 4.25 |
| 2018 | . | . | . | . | . | . |
| 2019 | . | . | . | . | . | . |

Source: Historical data based on national accounts (Columns 1 and 6), Supervisory reports (Columns 2 and 3) and MIR data (Columns 4 and 5). Projections are confidential and are based on the macro-econometric model developed at the Bank of Italy (Columns 1, 2, 3, 5, and 6) and on the 3-month Euribor futures (Column 4).

[29] For further details on macroeconomic inputs see Michelangeli and Pietrunti (2014).

**Stress tests**

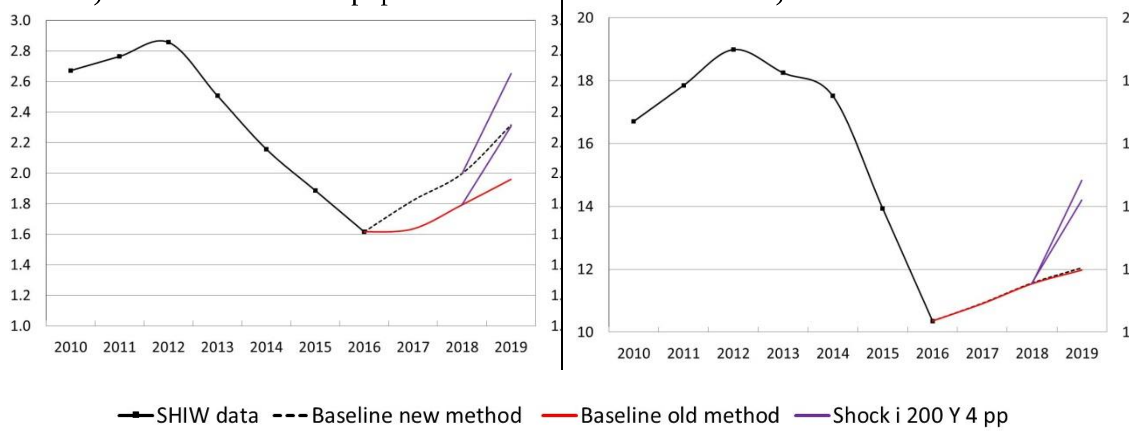
The model can be used to evaluate alternative and adverse scenarios for the financial conditions of indebted households.

For instance, with respect to the baseline scenario, we consider a very adverse scenario in 2019 with an increase of 200 basis points in the 3-month Euribor rate, in the 10-year IRS rate and in the consumer credit rate (Figure A.5). This increase affects both the payments associated with existing variable-rate loans and new loan originations. This shock is combined with a decrease of 4 percentage points in the growth rate of nominal income; the income shock affects all households. Relative to the baseline projections, the share of vulnerable households would be higher by about 0.3 percentage points and their debt by about 2.2 percentage points. The results of this simulation suggest that the conditions of Italian households would remain quite sound overall, even in more hostile conditions, as the vulnerability indicators would always remain below the levels reached in 2012.

**Figure A.5**

**Vulnerability in the period 2016-19 under adverse scenarios:**
**Interest rates stress (+200 bps) and income stress (-4 p.p.) in 2019**
*(percentages)*

a) Share of HHs in the population | b) Debt at risk




(1) Debt at risk refers to the share of debt held by vulnerable households.