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Mate Rosan and Krunoslav Zauder

Risky Business or Basic Needs Fulfilment? An Analysis of Croatian Households' Debt

Hotel "Grand Villa Argentina"
Dubrovnik
June 17, 2019

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CROATIAN NATIONAL BANK

Risky business or basic needs fulfilment?
An analysis of Croatian households' debt

Rosan Mate*[1], Zauder Krunoslav[2]

ABSTRACT

This paper analyses the main determinants of debt taking behaviour of households in Croatia, by using data from the *Household Financial and Consumption Survey* that was conducted for the first time in Croatia during 2017. The survey was developed and harmonized within the ECB's *Household Finance and Consumption Network* (HFCN). The particularly rich survey data structure allows us to link relevant individual and household socioeconomic characteristics, such as demographics, education, working status, information about the value and structure of households' assets, risk attitude as well as credit constraints with the debt taking behaviour of the household. Our estimates confirm the basic results stemming from the life-cycle hypothesis. Moreover, we identify the contribution of the self-reported risk attitude and credit constraints for the accumulation of consumer (non-mortgage) debt.

June 2019

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[1] Financial Stability Department, Croatian National Bank. e-mail: mate.rosan@hnb.hr *corresponding author
[2] Financial Stability Department, Croatian National Bank. e-mail: krunoslav.zauder@hnb.hr

Introduction

During the 2000s, the level of household borrowing has grown considerably in Croatia, both in absolute terms and in relative to income, resulting in average annual growth rate over 20% in the period between 2001 and 2008 (Figure 1). Similar rising household debt pattern was also present in other Central and Eastern Europe (CEE) countries, where since early 2000s household debt-to-GDP ratios had risen from levels at around 10 percent or less to over 40 percent in 2009[3]. While crisis and post-crisis period was characterized by a moderate fall in aggregate household debt (Figure 2), this phase was marked by difficulties in debt servicing capacity by a large number of households, due to particularly high debt levels. Namely, share of non-performing loans among Croatian households has reached relatively high levels and a substantial share of the population was in a situation of personal bankruptcy. This was, besides poor macroeconomic conditions, the result of foreign exchange risk, which materialized in loans denominated in Swiss franc[4].

In the most recent period household debt has gradually recovered, including a recent rise in non-collateralised loans as well as a moderate recovery of growth in housing loans. While the present growth is far from excessive, implying only moderate risk build-up in the economy, it is important to bear in mind that potential credit boom can result in a non-negligible number of over-indebted households, inflicting losses for the credit institutions and a fall in household welfare. The CNB has strong experience in the area of macroprudential policy as various measures have been effectively used in order to curtail the build-up of systemic risks related to strong credit growth in 2000s, including measures directed at household credit growth (Dumičić, 2017). However, these have mainly been top-down as well as lender-based. Gaining insight about the characteristics of indebted households could be useful for enhancing the borrower-based macro prudential toolkit available to CNB. Therefore, we employ a new source of borrower-based data from the *Household Finance and Consumption Survey* (HFCS), in order to determine the main drivers of debt taking. Since the total debt of a household consists of both secured (mortgage debt) and unsecured debt (non-mortgages), our aim is to understand the differences in determinants of holding each type of debt.

[3] One of the main engine of growth in 2000s was debt debt-financed consumption. This has sustained consumption growth and consequently contributed to the decline in household savings (Barba and Pivetti, 2009)
[4] More about Swiss francs on CNB press release „Some facts about loans in Swiss francs and some options for government intervention“, January 2015

The survey was developed and harmonized within the ECB's *Household Financial Consumption Network* (HFCN), and is regularly conducted in the euro area and some other EU countries using a standardized approach, with the third wave currently being finalized. During the spring of 2017, Croatia participated in the HFCS for the first time. Thus, all collected information represent a novelty for Croatia. HFCS dataset provides a rich new source of micro-level data on household finances and all other relevant information on socioeconomic and demographic characteristics of households, thus providing a sound basis for detailed analysis of household's debt holdings and their main determinants.

Compared to existing research the main contribution of our analysis is twofold. First, the use of detailed HFCS data provides information on household assets and liabilities allowing us to extend the analysis and investigate the household indebtedness in more detail, focusing on the recent period (2017). Secondly, we will identify which household characteristics are increasing the likelihood of debt taking. Moreover, this paper reveals the importance of risk aversion and credit constrains for non-mortgage debt accumulation. Furthermore, we explore differences in terms of financial and real assets influence on the likelihood to hold debt.

The paper is structured as follows. In the first section, we offer a literature review of similar research. In the second section, we present the HFCS data as well as offer descriptive statistics on debt market participation in Croatia. The third section presents the methodology and variables used in analysis. In the fourth section, we provide the results of various model specifications. The last section presents the main conclusions and possible directions for future research.

Literature review

Generally, theory explaining consumption behaviour is based on the life cycle assumption (e.g. Modigliani and Brumberg 1954), which describes how consumers allocate their time, money and effort in terms of borrowing, savings and consumption and how they make their life cycle choices. According to the life cycle theory, individuals make decisions to take over debt to "smooth consumption with regard to future income and wealth", thus maintaining a stable level of consumption throughout their lifetime. Bearing in mind that the income during a lifetime is hump-shaped, i.e. it is low at early ages and after reaching a mid-life peak it decreases, it is expected that younger households, at an earlier stage of life will have a higher debt market participation. This enables them to increase spending beyond the level that can be financed by current income. For this reason, the age of the household head and future income prospects is expected to have an important influence on the likelihood of assuming debt.

According to the literature, young people are keener to assume debt (Cox et al 2002) and their need for debt is increased until the household head reaches the mid-thirties and then it declines (Cox and Jappelli, 1993; Duca and Rosenthal, 1993). Crook (2001) finds that a household demands less debt when the head of household is over 55 years. Crook also showed that households over age 55 were less likely to be credit constrained. It is also interesting to note that in certain empirical works authors finds that debt increases with age (Yilmazer & DeVaney, 2005; Magri 2002).

The relationship between current income and the likelihood of borrowing in the literature is not uniquely determined. Namely, higher current income reduces the need for debt take on. However, with the increase in current income, demand for debt may increase, especially if there a permanent shock to income[5] (Friedman, Milton, 1957) for which an individual can expect to realize higher incomes throughout the life cycle, and accordingly increase their current consumption if needed[6]. Earlier, researchers showed that income plays an important role in affecting debt as individuals from higher income group can afford greater debts (Crook, 2006; Del-Río & Young; Petrides & Karagrigoriou, 2008; Fasianos et al. 2014). Magri (2002) finds that the role of income is important, with the uncertainty of income reducing the demand for loans.

Apart from age and income, other socioeconomic factors also affect the likelihood that households assume debt. Among them, family size was found as an important determinant of household debt in a large number of studies (Del Rio and Young, 2005, Crook 2006, Bover et al 2014; Brown and Taylor 2008; Xiao and Yao, 2011). The rationale behind this is that the greater the number of the household members the higher are the household expenses and consequently the greater is the likelihood for households to assume debt. Higher levels of education and employment status are also associated with a greater likelihood of holding debt (especially mortgage debt). Status in employment has a direct influence on debt participation,

[5] Agents look for life-time utility maximization, and change in consumption is not likely to occur due to a transitory change in income, but rather due to a permanent income shock (Friedman, 1957).

[6] PIH is disproved later by empirical evidence. Hall (1978) and Flavin (1981) found out that consumption was not determined solely by permanent income. Deaton (1992) discovered that consumption and current income are interdependent.

due to constraints on supply side of the market. Many empirical studies prove that employed and self-employed people are more likely to hold debts than retired or unemployed (Crook (2006). The same author finds that employment influences the amount of debt whereby those working in the public sector accumulate greater amounts of debt. Some studies show that there is a difference between assuming secured vs unsecured debt. Based on HFCS data, Bover et al. (2014) found that both secured and unsecured debts differ considerably across 11 euro area countries. Their evidence suggests that secured debt is more likely to exist in employed households. Many studies points to the level of education of the household members as an important factor of debt market participation. Education affects household debt positively as better education offers prospects of higher future income and "implies" higher financial literacy (Godwin, 1998; Kim and DeVaney 2001; Crook 2006, Brown and Taylor (2008).

Financial assets have a positive relationship with debt as they can be used as a mortgage for securing loans (Leonard & Di, 2014). Banks et al (2002), in analysing the distribution of debt and the financial wealth of British households, found that having unsecured debt is more likely for people with no financial assets. Fasianos et al. (2014) use HFCS data for five EU countries[7] and find that the likelihood of holding both types of debt decreases with higher levels of financial assets. Same authors find that real estate assets level has a significant and positive association with assuming secured debt. Home ownership is also found to be important in explaining debt as many people take housing loans. It is one of the major factors of rising household debt in many countries (Andrews, Sanchez, & Johansson, 2011; Del-Rio and Young 2005). Arvai and Toth (2001) find that in Hungary the future income expectations and past borrowing experience have positive effect on the propensity to borrow. Attitude towards risk of the household is expected to have an important role in the decision to borrow (Del Ro and Young, 2005; Godwin, 1997; Crook, 2001).

Up to our knowledge, there is a limited literature focusing on characteristics of indebted households as well as the implications for risks to financial stability in Croatia due to the lack of detailed household level debt data. However, notable exceptions are the papers by Herceg and Šošić (2011) as well as Herceg and Nestić (2014).

The work that is interesting in our context is Herceg and Šošić (2011), whereby they used the data from Households Budget Survey (HBS)[8] for 2005 and 2008. Using quantile regressions,

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[7] The countries under examination are Germany, Greece, Italy, Portugal and Spain.
[8] The objective of the Household Budget Survey is to obtain data on the level and structure of household consumption expenditures.

they find that current disposable income, age of the head of household and homeownership status are the most significant variables on the largest part of the debt distribution. Other interesting statistical significant variables are the sector of economic activity the head is working in as well as the type of work with respect to the usual working time (part time vs full time). Using Machado-Mata decomposition they showed that most of the debt build-up from 2005 to 2008 in Croatia was the result of more lenient lending standards on supply side and excessive consumption as a consequence of expectations of fast-growing incomes on other sides.

Data

Analysis geared towards researching personal debt should necessarily address the socio-demographic and economic characteristics of indebted individuals. In order to gain a better understanding of the specific characteristics of debt-taking agents in Croatia this paper uses micro level data from the current, third wave of Eurosystem's HFCS (*Household Finance and Consumption Survey*)[9], conducted for the first time also in Croatia. The HFCS is a standardised euro-wide survey, which primarily collects household-level data on various forms of assets, liabilities, household income and expenditure, as well as other socio-demographic information needed to analyse and understand economic decisions of the households.

In the survey conducted in the first half of 2017, 1.357 households successfully participated, which translates into a response rate of around 33.5%. As in all analyses using survey data, household survey weights are applied to account for unequal sampling probability and different probabilities of participation across households. Multiple stochastic imputations[10] of the missing data with respect to item non-response were made in accordance with ECB Multiple Imputation Routines (€MIR) before the dataset was made available. Thus, all survey results come in five versions (i.e. “implicates”) of the data which we consider when testing for the significance of the estimates.

We examine household debt participation under two surveyed categories: long-term mortgage debt (secured by residential property), usually taken for a period of 20 to 30 years, and short/medium term consumer debt (which is mostly unsecured). In the survey questionnaire,

[9] A complete methodological overview of the second HFCS wave can be found in ECB (2016).

[10] The assumption is that the non-response to a specified variable is MAR (*missing at random*) which means that non-response to a specified variable does not depend on an unknown value, but only on a set of selected independent variables. The imputation model, therefore, includes variables that explain the response process as well as variables correlated with the missing value.

households' liabilities are therefore divided into mortgage debt, consisting of mortgage loans secured by the main household residence (MHR) or other property, and consumer (non-mortgage) debt involving credit lines/overdrafts, credit cards and other non-mortgage loans.

According to HFCS data, nearly 41 percent of households in Croatia in 2016 were indebted, and the proportion is higher in the segment of non-mortgage loans. In fact, 32 percent of indebted households had only non-mortgage debt, 5 percent had only mortgage debt, while about 4 percent of households had both types of debt. On the other hand, the total amount of household debt is in the form of mortgages, because the associated amounts are much higher than for other consumer debt.

As the age of the household head increases, the need for extra debt diminishes and reaches the lowest levels at an older age when demographic factors that exert pressure on consumption growth are less pronounced. Looking at the level of annual household income, the share of debt-bearing household increases with higher income categories, reflecting greater debt servicing capacity and easier access to loans, given the lower perceived risk of lenders. The proportion of low-income households with a non-mortgage loan is much higher than the share of those with a mortgage loan, since the former type of debt is usually characterised by lower value and shorter maturity. In addition, non-mortgage debt is used to renovate, cover living expenses, or to refinance debt (Figure 1).

Working status of the household reference person[11] also matters, as employed and self-employed have higher debt. This may reflect easier access to loans, given the guarantee of a regular income, and is consistent with theories that uncertainty about future income reduces borrowing. Unemployed are less likely to take part in the credit market due to the constraint of low (or no) creditworthiness. Compared to the mortgage debt, unemployed and retired are more likely to hold "short-term" non-mortgage debt than long-term mortgage debt.

[11] The reference person is defined at the start of the survey in accordance with the Canberra definition (Canberra Handbook, UNECE, 2011). The definition uses the following sequential steps until a unique reference person in the household is identified: (i) takes into account household type, (ii) the person with the highest income; (iii) the eldest person.

Methodological background and variables used

In order to explore the characteristics of debt-taking households, we use two different probit model specifications. In them, we model the determinants affecting the likelihood that household holds either a mortgage or non-mortgage debt. In each of the specified models, a dependent variable can only have two values for each individual household:

$$Y_i = \begin{cases} 1, & Has\ \ debt \\ 0, & Doesn't\ have\ \ debt \end{cases}$$

and is the function of socio-economic and demographic characteristics of households. Our starting hypothesis is that household borrowing follows the life-cycle hypothesis so we examine the influence of the selected indicators constructed from the HFCS data: age of the reference person, number of dependent children, gross annual household income, gross wealth (either separately gross financial or/and real assets) and constructed variables based on the survey responses: risk attitude and credit constrained.

Household's gross income is represented by the sum of regular income received individually by its members (employee income, income from self-employment, income from pensions and other social benefits) and mutual household income (income from businesses and financial assets, rents on real estate and regular social and private transfers). Household assets are the sums of real assets and financial assets. Real assets are composed of the household main residence, other real estate property, vehicles, valuables and self-employment businesses. Financial assets includes deposits, bonds, shares, mutual funds, pension/whole life insurance etc.

Dummy variables are created for the classification of households according to the education level, the working status of the reference person and the risk-taking behaviour. The education levels are divided into two categories: completed tertiary education and the combination of basic and secondary education. The working status distinguishes employees (permanent position, employees with temporary contracts, self-employed workers) and other (unemployed, retirees and other inactive persons such as students and those dedicated to unpaid home tasks).

Furthermore, based on the answer to the question of how many financial risks household are willing to take we construct a dummy variable that assumes value 1 if households are willing to take any risks[12] when making financial decisions. We also include household self-assessed information on access to credit. Within this variable "direct" credit constraint is covered based on the answer to the question whether the household had applied for a loan or other credit and were turned down, within the last three years, as well as not been given as much credit as applied for. In addition to these directly constrained households, a broader measure of credit constraint is defined by also considering the “discouraged” households that did not apply for credit because of perceived constraints.

Since the dependent variable is binary, we use a probit model to estimate the likelihood that households with certain characteristics take on debt. Probit model is defined by a standard cumulative normal distribution function, and is used to model the regression function when the dependent variable is a binary (i.e. follows a Bernoulli distribution):

$$Pr\left(Y = 1|X_{1,}X_2, \dots, X_{k,}\right) = \phi(\beta_0 + \beta_1 X_1 + \beta_2 X_1 + \dots + \beta_k X_k)$$

$$\phi(z) = Pr(Z \leq z), Z \sim N(0,1)$$

We estimate five regressions, one for each of the data implicates. Estimated regression coefficients are then combined in order to get to the final estimates. Following the literature (see e.g. Rubin, 1987), the values of final coefficients are simply the averages of coefficients estimated for a particular data implicate[13]. Therefore, in the case of our probit model, we combine estimated coefficients ($\hat{C}_i$) using Rubin's rules and Rao and Wu’s (1988) rescaling bootstrap to calculate standard errors[14].

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[12] Respondents are asked whether they are willing to take (significant, above average or average) financial risks, as opposed to not being ready to take any financial risks.

[13] We express the average estimated coefficient $\bar{C}$ by: $\bar{C} = \frac{1}{N}\sum_{i=1}^{N} \hat{C}_i$

[14] Using replicate weights r = 1,…, R we derive the *within-implicate* variance $\widehat{W}_i$ which is:

$$\widehat{W}_i = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\left(\hat{C}_{ir} - C_{ir}\right)^2$$

The variance *between implicates* is: $B = \frac{1}{N-1}\sum_{i=1}^{n}\left(\hat{C}_i - \bar{C}\right)^2$

Total variance for the estimated coefficients is: $T = \overline{W} + \left(1 + \frac{n}{n-1}\right)B$

Estimated regression coefficient of the probit model points to the sign of an explanatory variable's significance, but does not indicate the effect that the unitary change of the exploratory variable has for a certain likelihood, therefore, we calculate marginal effects of the models that are estimated at the mean values of the explanatory variables (i.e. for an average household):

$$M_i = \frac{Pr(Y = 1|X)}{\partial \beta_k} = \varphi(X\beta)\beta_k$$

Results

The results from the probit models are presented in Table 2. They point to the inverse U shaped age curve, implying that the likelihood of having debt rises to the mid-40s when it slowly falls towards retirement age (Figure 4), which confirms the life cycle theory. There are several possible reasons for this hump-shaped pattern in case of Croatia. First of them is different preferences for borrowing across age cohorts, second is insufficient access to loans in the recent past since the retail market for mortgage loans developed quite recently in early 2000s. Last plausible reason could be the privatisation of dwellings in the 1990s, which enabled older households to become homeowners without needing to get mortgage debt.

The estimated impact of income on the likelihood of holding debt is statistically significant when it comes to taking over mortgage debt, with the likelihood of having debt being in a nonlinear relationship with income, in which case the likelihood for debt assumption is in a non-linear relationship with income. This implies that the marginal income effect depends on the level of household income itself because households with lower income levels potentially face limited access to credit. Results obtained by linear extrapolation show that the contribution of the level of income to the likelihood of taking on mortgage debt is positive only at the levels above HRK 100,000 annual gross income. Furthermore, education level is a significant determinant for taking over mortgage debt. This two regularities are interrelated, since more educated people also tend to have higher incomes. Namely, households whose reference person has higher education (tertiary level) have higher likelihood of having mortgage debt compared to households whose reference person is not educated or has only primary or secondary education.

Households might take debt to purchase assets, or have to own the property as collateral in the takeover of housing (mortgage) debt. We run two separately regression to examine their relationship with debt. Results indicate that higher level of gross assets increases the likelihood assuming mortgage debt, and in parallel decreases likelihood to assume non-mortgage debt. Controlling by the type of assets, we have demonstrated the positive contribution of real assets to the likelihood to assume mortgage debt. At the same time, financial assets do not play a statistically significant role in debt participation.

The mortgage debt prevalence increases with the number of dependent children. As the number of dependent children increases, it is more likely, that households will take over mortgage debt. The number of dependent children does not play a significant role in non-mortgage household borrowing. It seems that in terms of employment status a category that describes population being out of the labour market (retired, students, unpaid interns, out of workforce, permanently disabled, etc.) have significantly negative likelihood to participate on debt market.

Furthermore, the self-reported willingness of households to take any risks when making financial decisions also plays a significant role. Likelihood of taking over debt in the case of households that are ready to take over some level of financial risk compared to households that are not ready to take any financial risk is higher by 11 percentage points, while risk attitude does not play a significant role in mortgage household borrowing. Household self-assessed access to the credit market in the last three years (in terms of credit approval and/or the loan amount) indicating that credit constrained households have significantly higher likelihood to assume non-mortgage debt.

Conclusion

In this paper, we have employed new data from Household Finance and Consumption Survey, containing detailed information on Croatian households' finances. By using probit regression methodology, we have presented major socioeconomic as well as demographic characteristics contributing to household debt build-up.

In doing so, we established some of the basic results of life-cycle income theory. Namely, propensity to borrow peaks for cohorts in the middle of the age distribution both for mortgage and non-mortgage debt. When it comes to assets it has seems that real assets holdings is a significant determinant in assuming mortgage debt. Number of dependent children and the level of education are also positively associated with a greater likelihood of holding mortgage debt.

The results also suggest that the households with credit constraints in the form of inability to access the credit market or acquire the satisfactory level of debt have a higher probability of assuming non-mortgage debt. Furthermore, the self-reported willingness of households to take any risks when making financial decisions also plays a significant role. Households that are ready to take over some level of financial risk compared to households that are not ready to take any financial risk have higher likelihood to assume non-mortgage debt, while risk attitude does not play a significant role in mortgage household borrowing. This might prove that some households in Croatia enter into take more risk than they are able to withstand in case of the risk materialisation. It seems instructive to follow up on this result and to include other more detailed questions related to risk attitude in the future wave of HFCS in Croatia.

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Appendix

Table 1 Socio-economic characteristics of indebted households in Croatia

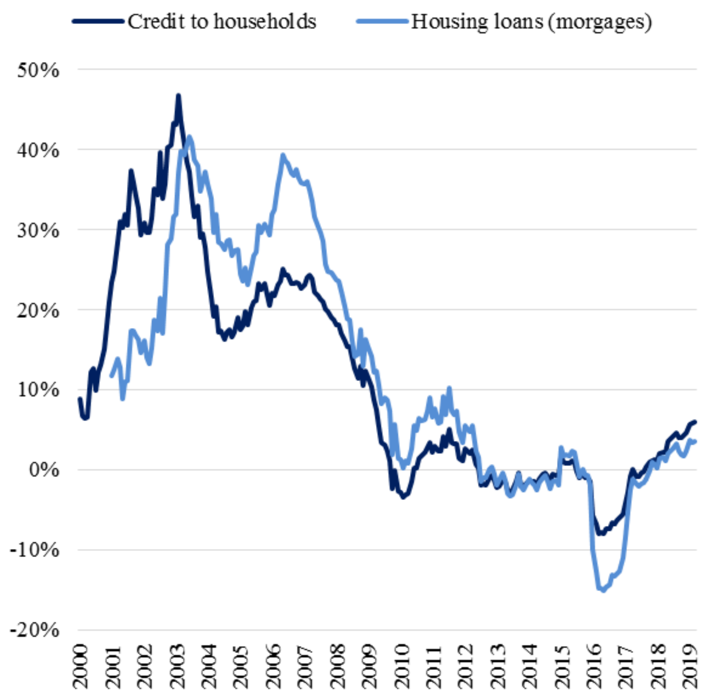
		Share (%) of households		
		Debt	**Mortgage Debt**	**Non-mortgage debt**
Total		40,7	9,0	35,8
Household size	1 member	24,0	2,7	22,7
	2 members	36,2	7,1	33,2
	3 members	50,0	9,5	45,6
	4 members	52,3	17,2	40,9
	5+	53,4	13,5	45,4
Age of RP	16-34	42,0	7,1	38,2
	35-44	62,7	17,3	50,0
	45-54	45,6	14,3	40,4
	55-64	44,5	7,6	40,3
	65-74	27,4	3,3	25,7
	75+	16,1	1,4	15,5
Education of a RP	Primary or none	29,5	2,8	27,9
	Secondary	43,5	9,6	37,8
	Tertiary	47,5	16,5	40,2
Employment status of the RP	Employed	53,3	14,0	44,8
	Self-employed	55,3	22,6	52,6
	Unemployed	32,6	7,6	30,0
	Retired	29,9	3,6	27,8
	other	8,0	0,0	8,0
Income Quintiles	Lower 20%	27,2	4,0	25,2
	20% to 40%	29,6	3,8	27,2
	40% to 60%	42,8	8,3	38,2
	60 to 80%	54,1	12,1	49,1
	80 to 100%	50,4	17,2	39,4
Net Assets Quintiles	Lower 20%	45,8	4,6	42,5
	20% to 40%	38,9	9,5	33,8
	40% to 60%	41,5	11,5	34,7
	60 to 80%	42,2	9,4	37,9
	80 to 100%	35,2	10,2	29,9

Table 2 Marginal efects from Probit model

	Mortgage Debt				Non-mortgage debt			
	Model 1		***Model 2***		***Model 3***		***Model 4***	
	ME	*SE*	*ME*	*SE*	*ME*	*SE*	*ME*	*SE*
Age	0,0089***	*0,003*	0,0071**	*0,003*	0,0170**	*0,008*	0,0173**	*0,008*
Age^2	-0,00009***	*0,000*	-0,00008***	*0,000*	-0,0002***	*0,000*	-0,0002***	*0,000*
Num. of dependent children	0,0152**	*0,007*	0,0102*	*0,006*	0,0183	*0,021*	0,0374	*0,048*
Education: Tertiary	0,0322**	*0,015*	0,0278**	*0,013*	0,0475	*0,049*	0,0167	*0,021*
LMS: Unemployed	-0,0108	*0,028*	-0,0100	*0,024*	-0,1264	*0,079*	-0,1439	*0,096*
LMS: Retired	-0,0140	*0,019*	-0,0120	*0,017*	-0,0036	*0,059*	-0,0042	*0,059*
LMS: Other	-0,3738***	*0,078*	-0,3161**	*0,069*	-0,2663	*0,100*	-0,4001*	*0,241*
Risk attitude: Take risks	-0,0002	*0,013*	-0,0065	*0,011*	0,1289***	*0,042*	0,1213***	*0,040*
Credit constrained: Yes	-0,0341	*0,027*	-0,0284	*0,024*	0,1528**	*0,067*	0,1419**	*0,061*
Log(Income)	-0,0163*	*0,009*	-0,0102	*0,008*	0,0099	*0,031*	0,0132	*0,030*
Log(Income)^2	0,0018*	*0,001*	0,0011	*0,00081*	-0,0012	*0,003*	-0,0016	*0,003*
Gross Assets: 3-4th quintile	0,0556***	*0,015*			-0,0136	*0,041*		
Gross Assets: 5th quintile	0,0448**	*0,019*			-0,1134**	*0,044*		
Log (Financial assets)			-0,0006	*0,002*			-0,0029	*0,005*
Log (Real assets)			0,0183**	*0,004*			-0,01004	*0,006*

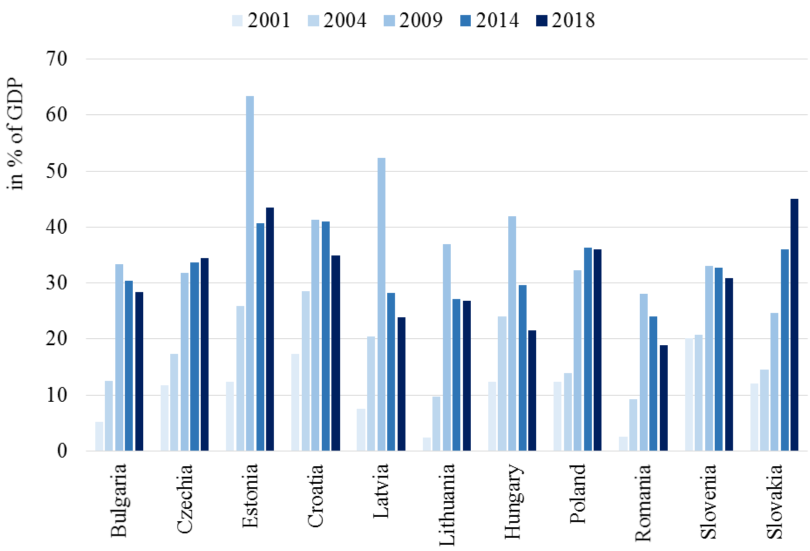
ME – marginal effects, SE – standard error,∗p < .1;∗∗p < .05;∗∗∗p < .001

Figure 1 Growth rates of credit to households 2000-2019



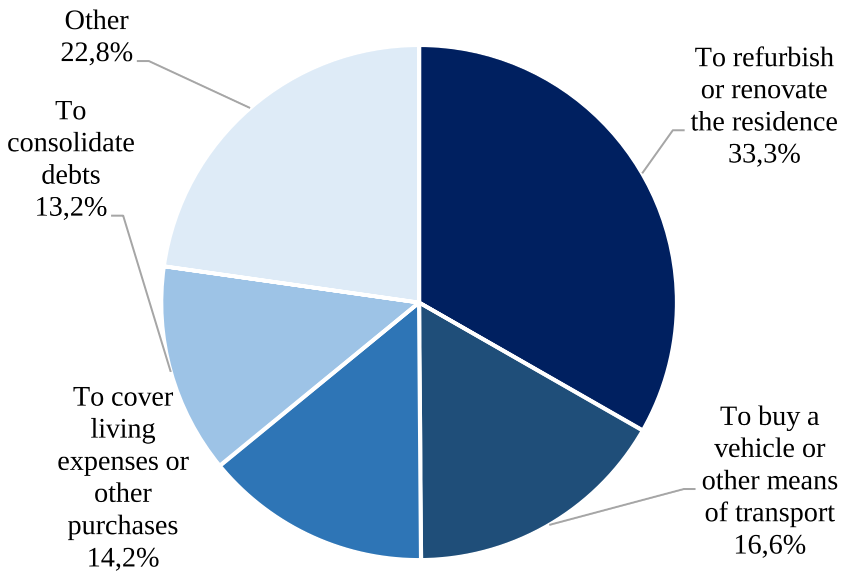
Source: CNB.

Figure 2 Household debt-to-GDP ratio in CEE countries, 2001–2014



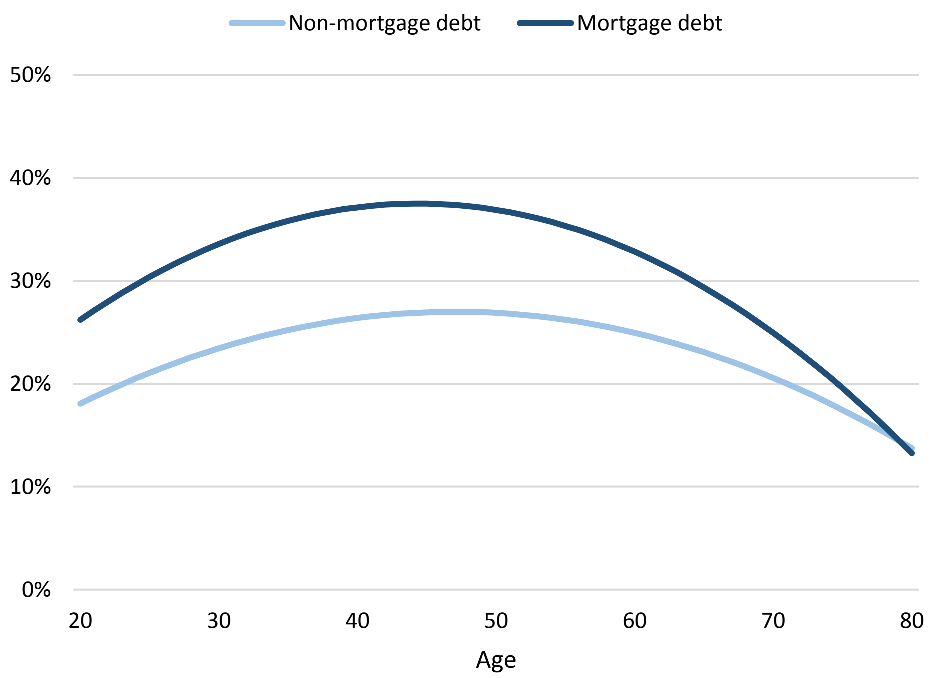
Source: Eurostat

Figure 3 Reasons for taking over non-mortgage debt



Source: authors' calculations based on the HFCS

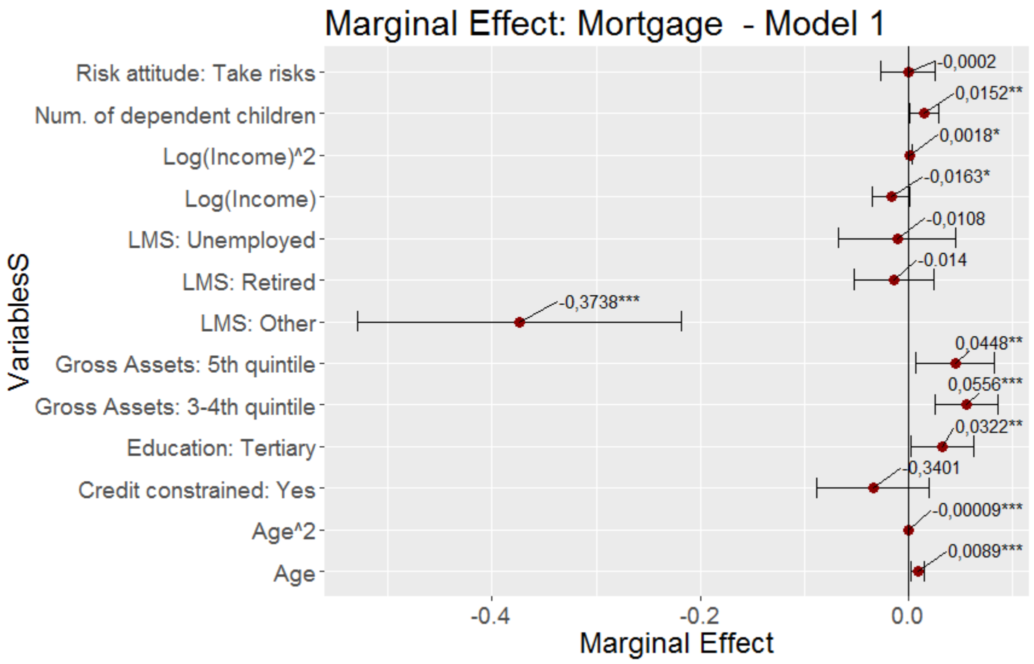
Figure 4 Influence of age on likelihood of having debt



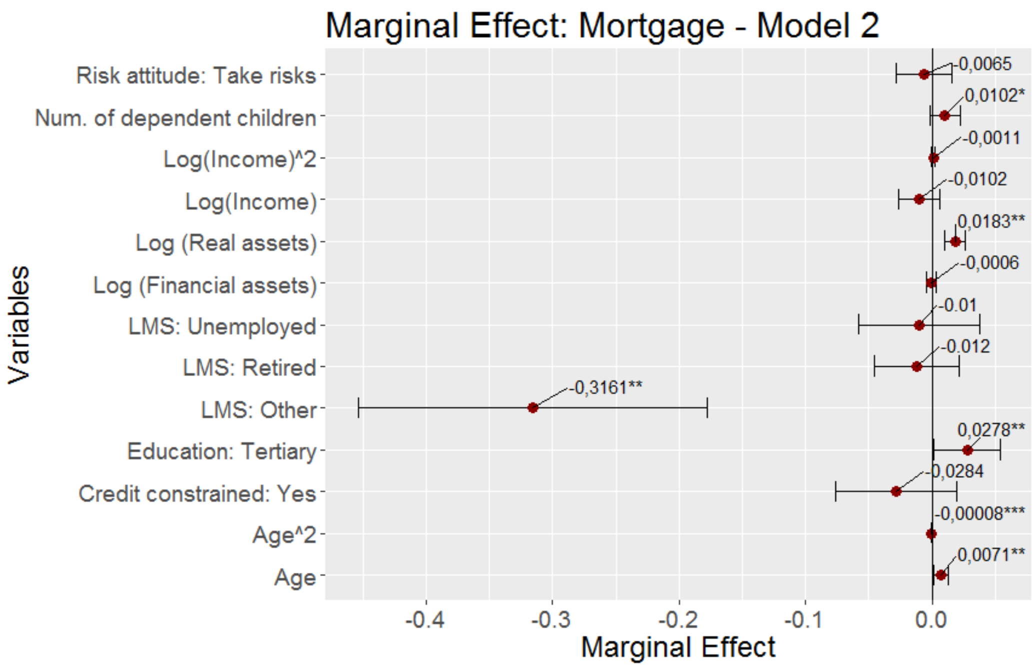
Source: authors' calculations based on the HFCS.

Figures 5. Graphical representation of marginal effects

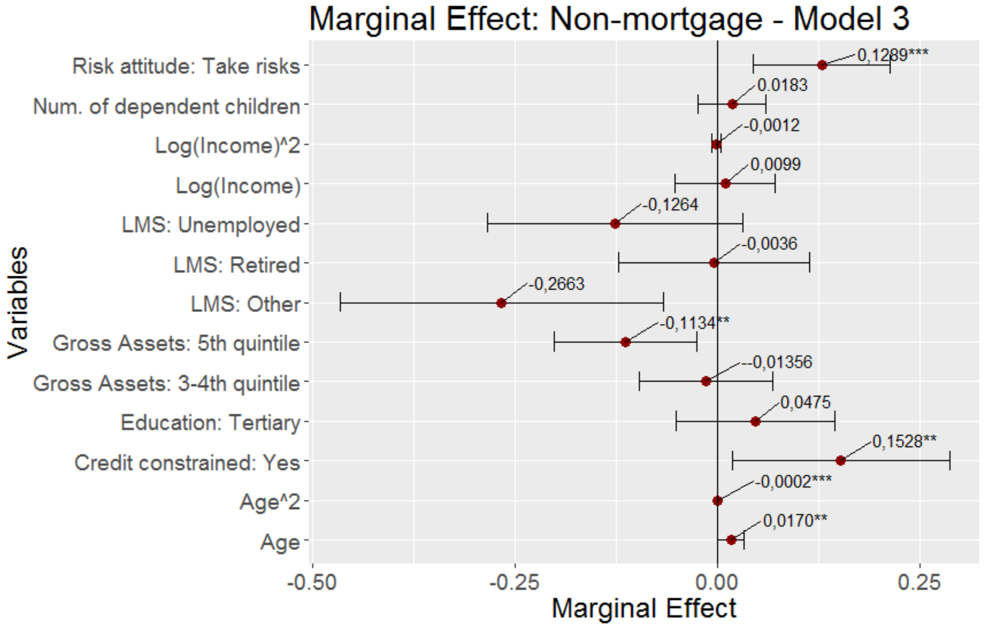
a)



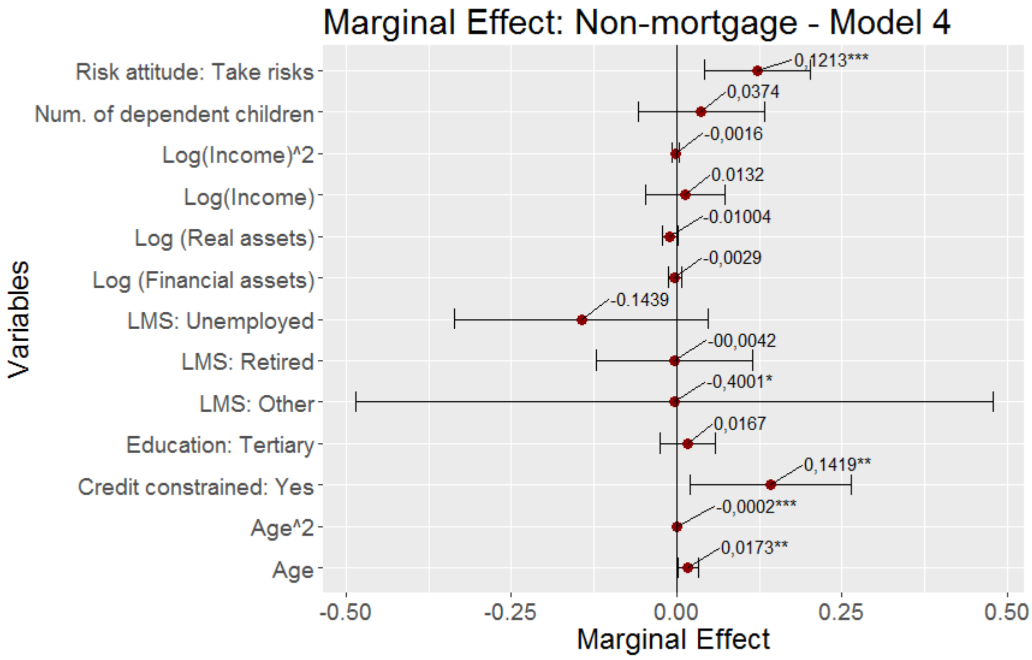
b)



c)


Marginal Effect: Non-mortgage - Model 3
Risk attitude: Take risks
Num. of dependent children
Log(Income)^2
Log(Income)
LMS: Unemployed
LMS: Retired
LMS: Other
Gross Assets: 5th quintile
Gross Assets: 3-4th quintile
Education: Tertiary
Credit constrained: Yes
Age^2
Age
0,1289***
0.0183
-0,0012
0,0099
-0,1264
-0,0036
-0,2663
-0,1134**
--0,01356
0,0475
0,1528**
-0,0002***
0,0170**
Variables
-0.50
-0.25
0.00
0.25
Marginal Effect

d)


Marginal Effect: Non-mortgage - Model 4
Risk attitude: Take risks
Num. of dependent children
Log(Income)^2
Log(Income)
Log (Real assets)
Log (Financial assets)
LMS: Unemployed
LMS: Retired
LMS: Other
Education: Tertiary
Credit constrained: Yes
Age^2
Age
0,1213***
0,0374
-0,0016
0.0132
-0.01004
-0,0029
-0.1439
-00,0042
-0,4001*
0,0167
0,1419**
-0,0002***
0,0173**
Variables
-0.50
-0.25
0.00
0.25
0.50
Marginal Effect

Risky business or basic needs fulfilment? An analysis of Croatian households' vulnerability

Mate Rosan[1], Krunoslav Zauder*[2]

ABSTRACT

In this paper, we employ a new household-level data source detailing Croatian households' finances (*Household Finance and Consumption Survey*) in an attempt to identify vulnerable households as well as find the characteristics associated with higher vulnerability. Our approach consists of using a latent class cluster model in order to group households with respect to vulnerability as well as using a limited dependent variable model of a probit type to look for the factors which may have contributed to the household becoming vulnerable. We identify 14% of indebted households in our sample as vulnerable and find that the most significant contribution to the vulnerability comes from having a housing (i.e. mortgage) loan. We find three possible channels of this influence, either through the fact of having a mortgage alone, due to higher amounts of debt and debt service, or through other mortgage indebtedness characteristics such as having mortgages with adjustable rates or a mortgage denominated in foreign currency, and/or having taken a mortgage in the period of the most significant household debt build-up in Croatia, from 2005 to 2008, which was in previous domestic research identified as reflecting risk seeking behavior by borrowers and lenders.

Key words: household vulnerability, mortgage debt, debt cycles, adjustable rates, HFCS

June, 2019
Draft version
Please do not quote

[1] Financial Stability Department, Croatian National Bank. e-mail: mate.rosan@hnb.hr
[2] Financial Stability Department, Croatian National Bank. e-mail: krunoslav.zauder@hnb.hr *corresponding author

1. Introduction

Household debt represents around one third of assets held by credit institutions in Croatia, which makes the dynamics of credit to households an important factor contributing to the stability of the financial system. For this reason, it is important to try to understand the factors influencing the sustainability of the household debt build-up, which we attempt in this paper, by examining the possible sources of the vulnerability of their finances.

First significant households' debt build-up began in the 2000s (Figure 1) and mostly manifested itself through increased mortgage borrowing. The growth in credit to households was accompanied by solid economic growth and averaged almost 20% in the peak period 2005-2008. Furthermore, a large part of the economic growth came from the construction sector, and was accompanied by rising residential real estate (RRE) prices. This fueled optimistic expectations about future RRE prices as well as future incomes, significantly contributing to the willingness to borrow in order to buy RREs. The accumulation of credit risk in the 2000s was further stimulated by the developments in the banking sector, with banks becoming more willing to lend, particularly with adjustable rates, as well as in foreign currency, possibly reflecting more lenient standards (Herceg & Šošić, 2011). The "bubble" of the 2000's came to an end in the aftermath of the subprime mortgage crisis in the US and the start of the great recession.

The crisis and post-crisis period was characterized by the prolonged deleveraging of the household sector and a moderate fall in aggregate household debt levels, accompanied by sluggishness in domestic consumption. In the most recent period household debt is gradually recovering, including a rise in non-collateralized loans as well as a mild recovery of housing loans' growth, accompanied by a moderate rise in RRE property prices.

While the present growth is far from excessive, implying only moderate risk build-up in the economy it is wise to try to understand the consequences of the previous credit developments in Croatia, since a potential credit boom can result in a non-negligible number of over-indebted households, inflicting losses for the credit institutions and a fall in household welfare. The CNB has experience in the area of macroprudential policy as various measures have been effectively used in order to curtail the build-up of systemic risks related to strong credit growth in 2000s, including measures directed at household credit growth (Dumičić, 2017). However, these have mainly been top-down as well as lender-based. Gaining insight about the consequences rapid credit growth of the 2000s had on the sustainability of individual households' debt could help further the understanding of the effects of macroprudential measures used by the CNB as well as give implications for their future use.

Particularities of debt sustainability could be analyzed by looking at the characteristics of vulnerable (i.e. over-indebted) households, which is the topic of this paper. In order to be able to do so, we employ a new source of borrower-based household level data, *Household Finance and Consumption Survey* (HFCS), which has for the first time been conducted in Croatia, taking place during the spring of 2017. It provides a rich new source of micro level data with the specific aim of capturing information on household finances.

We attempt to distinguish socioeconomic, indebtedness (e.g. the types of debt a household holds) and other characteristics contributing to the likelihood of a household being vulnerable. We define household vulnerability as a state in which, due to a significant debt and debt service amounts in comparison to the household's income and assets, it is either unlikely to be able to service its debt or it will be sufficiently difficult for the household to do so[3]. From a financial stability perspective, this is important because household vulnerability can cause losses to the credit institutions as well as reinforce the negative effects of an economic downturn, by forcing over-indebted households to make larger cuts in spending[4] (Bunn & Rostom, 2015; Mian & Sufi, 2018). Our empirical strategy consists of using a latent class cluster model in order to identify vulnerable households in our sample and, once identified, finding characteristics or factors which may have contributed to the household becoming vulnerable by using a limited dependent variable model of a probit type.

The paper is organized as follows. In the first section we offer a review of similar research. In the second section we present the HFCS data as well as offer descriptive statistics on vulnerable households in Croatia. The third section presents the methodology and variables used in analysis. In the fourth section we provide the results of various model specifications. The last section presents the main conclusions and possible directions for future research.

2. Literature review

Since the establishment of ECB's *Household Finance and Consumption Network* (HFCN) in 2006, a significant part of research has been oriented towards the analysis of household vulnerability within and across EU countries, usually in the function of establishing a framework for stress-testing as well as the calibration of macroprudential policy measures. In this short review we focus on a subset of available research and the implications for household vulnerability. The research available has been focused on describing socio-economic, demographic and other factors contributing to the ratios measuring debt burden (Costa & Farinha, 2012; Giordana & Ziegelmeyer, 2017), probability of a household being vulnerable, identified either through indebtedness ratios exceeding predefined thresholds or the subjective evaluation of the household itself (Albacete & Lindner, 2013; Du Caju, et al., 2016; Costa & Farinha, 2012), or to the probability of default (Ampudia, et al., 2014; Costa, 2012).

With respect to demographic characteristics, some researchers find that age of the household's reference person is negatively associated with the vulnerability indicators when regressing on indebtedness ratios such as debt-service-to-income (DSTI) as well as debt-to-income (DTI) (Giordana & Ziegelmeyer, 2017; Costa & Farinha, 2012) while contributing to the probability of the DTI ratio exceeding 300% (Costa & Farinha, 2012; Du Caju, et al., 2016) or negatively contributing to the probability of the debt-to-asset (DTA) ratio exceeding 75% (Costa & Farinha, 2012). Similar mixed results could be found for the education level of the reference person (Costa, 2012; Costa & Farinha, 2012; Du Caju, et al., 2016), while being unemployed contributes to the probability of a household's DTA ratio exceeding 75% (Albacete & Lindner, 2013), DTI ratio exceeding 300% (Du Caju, et al., 2016) and to the household's probability of default (Ampudia, et al., 2014; Costa, 2012). Likewise, household size is sometimes found to

[3] We operationalize this idea by using three ratios measuring debt burden: debt-to-assets (DTA), debt-service-to-income (DSTI) as well as debt-to-income (DTI), as described in the methodology section of the paper.

[4] According to the life-cycle theory of consumption, rational households choose lifetime consumption profiles as to maximize their expected utility over the lifecycle (Modigliani & Brumberg, 1954). In this respect they may wish to frontload their consumption by taking on debt, e.g. to buy their home. However, they will do so without leaving their lifetime utility unchanged. If a household makes a decision to take on debt based on wrong expectations it will end up reducing its future consumption by more than would be in line with its lifetime utility maximization. In this respect, to the degree that misplaced expectations are systematic, ending up over-indebted can be considered as an "investment mistake" (Campbell, 2006).

contribute to the probability of a household's DSTI and DTI exceeding chosen thresholds (30% and 300% respectively) (Du Caju, et al., 2016).

When looking at income, it is often found to contribute negatively to the vulnerability of a household measured either by the effect on indebtedness ratios (Costa & Farinha, 2012; Giordana & Ziegelmeyer, 2017), or through the negative contribution to the probability of a household being vulnerable (Costa & Farinha, 2012; Du Caju, et al., 2016) or to the probability of default (Costa, 2012). Similarly, wealth is found to negatively contribute to a household's probability of default (Ampudia, et al., 2014; Costa, 2012) and, as expected, DTA based vulnerability measures (Costa & Farinha, 2012) while positively contributing to DTI and DSTI based measures (Costa & Farinha, 2012), possibly reflecting the potential of households to finance their debt obligations from their wealth, if needed.

With respect to the characteristics of household's indebtedness, the results of available research indicate that having a mortgage increases DTA, DTI and DSTI ratios (Giordana & Ziegelmeyer, 2017) as well as contributes to the probabilities of DTI and DSTI being above 300% and 30% thresholds (Du Caju, et al., 2016). Furthermore, having both mortgage and other debt, as opposed to having only mortgages, is sometimes associated with higher values of the DTI, DSTI and DTA ratios as well as the probability of these ratios exceeding defined thresholds (Costa & Farinha, 2012). Conversely, other research finds that having non-mortgage debt contributes to the probability of being vulnerable either by DTA exceeding 75% or as subjectively perceived by the households (Albacete & Lindner, 2013) as well as contributing to the probability of default (Ampudia, et al., 2014).

As can be seen, the results of the contributions of various characteristics to household vulnerability, defined in various ways, are mixed, possibly reflecting country and definition differences, among others. Accordingly, in the rest of this chapter we focus on the contributions from the domestic literature. A significant obstacle in identifying vulnerable households in Croatia as well as their characteristics has been the lack of detailed household level financial data. This has resulted in a somewhat small quantity of domestic research focusing on the characteristics of vulnerable households as well as the implications for risks to financial stability. However, among the available domestic research, notable exceptions are the papers by Herceg and Šošić (2011) as well as Herceg and Nestić (2014).

While they do not analyze vulnerable households *per se*, research done by Herceg and Šošić (2011) is related to our work, since it provides the context for interpreting our results. Herceg and Šošić (2011) use household level data from the *Household Budget Survey* (HBS) for years 2005 and 2008. They employ a quantile regression to find household characteristics predicting indebtedness for the two periods as well as a Machado-Mata decomposition to distinguish whether changes in household aggregate indebtedness between 2005 and 2008 could be attributed to improved households' characteristics (i.e. creditworthiness) and those attributed to more lenient banks' lending policies and/or increased household propensity to borrow (reflecting overly optimistic expectations about future debt servicing capacity). Out of 27% increase in aggregate household indebtedness, Herceg and Šošić find that only 6% (at best) could be attributed to improved household characteristics, implying risk seeking behavior either or both on the side of credit supply as well as credit demand.

Herceg and Nestić (2014) use pooled HBS data to analyze the determinants of household vulnerability for the 2008 to 2010 period and provide the methodology for the identification of vulnerable households by employing latent class cluster analysis which we employ here as well. In this respect, they use financial margin, debt repayment burden as well as the Likert-based self-assessment of the household's financial situation as indicator variables. In the second step, they use logistic regression to find that income, age, the number of children as well as having a housing loan are among significant predictors of the vulnerability of an average household's finances. The main limitation encountered by Herceg and Nestić is the lack of detailed financial data available in Household Budget Survey, while the respectable sample size of almost 3000 indebted households makes their analysis relevant. It is worth mentioning that our approach, strongly inspired by Herceg and Nestić, differs in two respects. As indicators, we use DTI, DSTI and DTA defined as binary variables (whether or not they exceed the "usual" thresholds), while Herceg and Nestić used continuous indicator variables, including a subjective measure. Furthermore, in "determining" the characteristics associated with vulnerability, we include mortgage loans characteristics such as currency denomination and interest rate type as well as the period of origination to inform our conclusions.

3. Data

Household Finance and Consumption Survey[5] (HFCS) is regularly conducted in the euro area and some other EU countries using a standardized approach, with the third (2016-2017) wave, which includes Croatia for the first time, currently being finalized. The data included in the HFCS contains detailed information on household finances, including various forms of real and financial assets, private businesses, income from various sources, different forms of liability and debt service as well as consumption and other information, such as demographics and attitudes.

The survey for Croatia was conducted in the first half of 2017, with the data on flows reflecting the state of affairs in 2016, while stocks refer to the end of 2016. The whole sample includes observations on 1357 households with the missing data on key variables being multiply imputed, consequently providing five versions (i.e. "implicates") of each observation, to be taken into account when calculating the variance of summary statistics as well as model estimates. Personal variables, such as age, education or labour status are represented through the household's reference person (RP), identification of which is based on Canberra definition (United Nations, 2011), although this information is available for every member of the household.

With respect to debt, the survey provides details on mortgage debt, including information such as interest rate and currency type as well as the year of origination. We equate mortgages with housing loans, because a housing loan in Croatia typically (almost exclusively) includes real estate as collateral, while general-purpose loans approved with mortgages constitute only a small part (around 1%) of total credit to households in Croatia. Other debt is represented through non-collateralized loans, containing somewhat less detail, such as the length of loan at origination, but also through credit cards and overdrafts for which only the outstanding amounts are included. Consequently, only 60% of indebted households have regular debt installments ("annuities"), necessary for calculating DSTI ratios. Generally, in the survey sample, 41% of households hold debt, 32% hold only non-mortgage debt, 4% have both types of debt and 5% have only mortgage debt. With respect to the amounts, most of the debt is in the form of mortgages, around 65%.

[5] Third wave has not yet been completed in all of the participating countries. A complete methodological overview of the second HFCS wave can be found in European Central Bank (2016).

For the purpose of identifying and analyzing vulnerable households we chose only those households which are indebted in each of the data implicates, leaving us with a subsample of 468 households which includes 128 households with mortgages, 403 with other debt, including some overlapping as noted in the previous paragraph.

4. Methodological background and variables used

As mentioned earlier in the paper, the estimation procedure we use consists of two steps. In the first step, we aim to identify vulnerable households using a latent class cluster model. Subsequently, in the second step, we use various probability model specifications in order to find the socioeconomic and indebtedness characteristics associated with higher or lower probability that an average household in our sample is vulnerable.

In order to identify vulnerable households, we construct three indicator variables based on three ratios commonly used to measure households' debt burden: debt-to-asset (DTA) ratio, debt-to-income (DTI) ratio as well as debt-service-to-income (DSTI) ratio. Based on the actual values of the ratios as well as thresholds we found are commonly used in the literature, we construct three binary indicators: whether or not the household's DTA is above 75%, DTI above 300% or DSTI above 40%.

Having defined the three binary indicator ("manifest") variables, we proceed by performing a latent class cluster analysis (LCA) and assume two latent classes: "vulnerable" and "non-vulnerable". In doing so, we follow the approach defined in Linzer and Lewis (2011, 2013). Accordingly, latent class cluster analysis is deemed useful for the investigation of the "sources of confounding" between observed categorical data in order to "identify and characterize clusters similar cases" (Linzer & Lewis, 2013). In this respect, the model "probabilistically groups each observation into a "latent class" (i.e. vulnerable or not, *authors' comment*), which in turn produces expectations about how that observation will respond on each manifest variable."

The latent class cluster model estimates the expected probabilities of observing the k^{th} response to the j^{th} variable that an observation in class $r = 1 \ldots R$ produces[6]. This probability is denoted by π_{jrk}. The second parameter estimated is $p_{\ r}$, the proportions of observations in different classes. Based on the estimates of the parameters, one can calculate the posterior probabilities that each individual belongs to a particular class using the Bayes approach:

$$\hat{P}\left(r \middle| Y_i\right) = \frac{\widehat{p_r}\, f\left(Y_i, \hat{\pi}_r\right)}{\sum_{q=1}^{R} \widehat{p_q}\, f\left(Y_i, \hat{\pi}_q\right)},$$

where $f\left(Y_i, \pi_{\ r}\right) = \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{\ jrk})^{Y_{ijk}}$ denotes the probability that the i^{th} respondent in the r^{th} class gave a particular set of responses to the indicator variables. The latent class model is estimated by maximizing the log-likelihood function:

$$\ln L = \sum_{i=1}^{N} \ln \sum_{r=1}^{R} p_{\ r} \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{\ jrk})^{Y_{ijk}},$$

[6] The rest of the LCA description in this chapter is based on (Linzer & Lewis, 2013) as well.

with respect to π_{jrk} and $p_{\ r}$ using the expectation-maximization algorithm, where Y_{ijk} takes the value of 1 if the i^{th} respondent gave the k^{th} response to the j^{th} variable, and zero otherwise. The procedure is iterative, updating the values of the estimated parameters until the highest value of log-likelihood is reached and each individual is assigned to the class with the highest posterior probability.

Having classified the households to one of the two latent vulnerability groups ("vulnerable" and "non-vulnerable"), we aim to explore the association of various household characteristics or other factors with the fact that a household is vulnerable. We operationalize this through the limited dependent variable model of a probit type where the dependent variable, termed vulnerability, is binary and takes the value of 1 if the household was identified as vulnerable and zero otherwise. The probit model approach uses the assumption that the probability of a household being vulnerable can be modelled as a latent variable that follows a standard cumulative normal distribution function (Wooldridge, 2012):

$$Pr(Y = 1|\boldsymbol{X}) = \mathrm{G}(\boldsymbol{\beta X}), \qquad z = \boldsymbol{\beta X}$$

$$G(z) = \phi(z) = \int_{-\infty}^{z} \varphi(v)\mathrm{d}v\,, \qquad \varphi(z) = (2\pi)^{-1}\exp(-\frac{z^2}{2})$$

Accordingly, we model the probability of a household being vulnerable as a function of socioeconomic and indebtedness characteristics. We use the "survey" package for R programming language (Lumley, 2010) and run five regressions, for each of the data implicates. Rao and Wu's (1988) rescaling bootstrap replicate weights are implemented to calculate standard errors and derive the *within-implicate* variance. The results of the regressions are then combined, using "Rubin's rules" in order to get to the final estimate (Phillips Montsalto & Yuh, 1998). We present the results using marginal effects at the means of independent variables (Greene, 2012) whereby the marginal effects for the continuous independent variables are interpreted through a unit increase of the independent variable, while the marginal effects for discrete independent variables are interpreted with respect to the omitted categories.

In order to investigate possible influences on the probability of a household being vulnerable, we define two sets of independent variables used in the estimations: socioeconomic and indebtedness characteristics. Socioeconomic characteristics include the age and gender (coded 1 for female) of the reference person, household size as defined by the OECD equivalence scale[7] as well as education, which takes the value of 1 if the household reference person has tertiary education, as opposed to having primary or secondary education. Furthermore, we include two variables for the labor market status: whether the reference person is unemployed, or whether it is outside of the labor force, being retired, student or other. The labor market status variables are interpreted against the omitted categories: being employed or self-employed. Furthermore, we include a dummy variable reflecting whether the residence of the household is in the urban area, as well as a risk attitude dummy, coded 1 if the reference person of the household is willing to take any risks[8]. Household income and gross wealth are included as logs and are equivalised when omitting household size.

[7] 1+ (additional Household members aged 14 or more -1)*0.5 + (Household members aged 13 or less)*0.3

[8] Respondents were asked whether they are willing to take significant, above-average, average or no financial risks when making investment decisions. Since the bulk of the responses in our sample is concentrated in the no risk category (299 of 468 households), we grouped the first three categories to reflect the willingness to take "any risks".

On the other hand, we check for the influence of the households' indebtedness characteristics. We define two categories: households that have only mortgage debt and households that have both mortgage and non-mortgage debt, with both categories being opposed to households having non-mortgage debt only. In an alternative specification, we include a mortgage dummy. The mentioned categories are included in the two specifications that include the whole set of socioeconomic variables described in the previous paragraph. In addition, we run a separate set of regressions which include a debt installment control dummy, since 40% of households in our sample do not have regular debt installments as well as various mortgage characteristics: whether the household has taken a mortgage in the 2005-2008 or post 2008 period, whether the household holds mortgage debt with adjustable or fixed interest rates, and whether the household has a mortgage denominated in foreign or domestic currency. The three mortgage characteristics take the value of 1 if the household has a mortgage with the defined characteristic and zero otherwise. This means that for the households that don't have mortgages the binary variables take the value of zero (e.g. both when looking at adjustable and fixed rate mortgages), reflecting the fact that we don't make any assumptions about their debt characteristics, details for which are not available in our data set.

5. Results

The results of the latent class cluster analysis are presented in Table 2, giving the class conditional outcome probabilities as well as the proportion of vulnerable households identified in this way. We have identified 14% of indebted households in our sample as vulnerable with the dominant indicator being the debt-to-income (DTI) ratio. A vulnerable household has an 85% probability of having DTI ratio above 300%, a 59% probability of having debt-service-to-income (DSTI) ratio above 40% as well as a 24% probability of having the debt-to-assets (DTA) ratio above 75%. While these probabilities are significantly higher for the vulnerable class than for the non-vulnerable, they also reflect the fact that various indicators capture different households and that none of the used indicators is by itself sufficient to identify households with vulnerable finances.

Having categorized the indebted households with respect to the vulnerability of their finances, we proceed by providing the distributions of the two classes with respect to various socioeconomic and indebtedness characteristics. The distribution with respect to socioeconomic characteristics is given in Table 1. The most striking difference in the distributions of the two classes is with respect to the household income, whereby vulnerable households are concentrated in the lowest income quintile, a fact that is not surprising, given the importance of DTI and DSTI indicators in identifying vulnerable households. Therefore, we include the log of household income in our regressions as a control variable.

The results of the regressions of socioeconomic variables on the probability of being vulnerable are given in Table 3a. The specifications differ only in the way indebtedness characteristics are defined, with the omitted category referring to households that don't have mortgages. As expected, income is highly significant. With respect to other socioeconomic characteristics, we find that the rise in the household size increases the probability of being vulnerable, as well as that being outside of the workforce reduces it, reflecting the possibility of the household head being in the late phase of the life-cycle (retired), having already paid its debts, or too early (e.g. student), not yet having assumed significant amounts of debt. It should be noted that the household size as well as the labour market status "retired and other" are significant only on a 10% level.

The most significant contribution to the probability of being vulnerable comes from the indebtedness characteristics, whereby households with mortgages have a much higher probability of being vulnerable than households without them. This result is not surprising due to the high amounts of debt and debt service associated with having a mortgage debt. In this respect, we try to identify mortgage characteristics particularly contributing to the probability of being vulnerable. We begin with the descriptive statistics provided in Figures 2 and 3. Accordingly, vulnerable households are much more likely to hold mortgage debt and a bit more likely to hold both types of debt (2a). Furthermore, vulnerable households are a bit more likely to have taken a mortgage in 2005-2008 as well in post 2008 periods (Figure 2b). With respect to other mortgage characteristics, vulnerable households are somewhat more likely to hold mortgages with adjustable interest rates (2c) as well as a bit more likely to have mortgages denominated in a foreign currency (2d). The importance of the 2005-2008 period for the outstanding amounts of household mortgage debt at the moment of the survey conduction (spring of 2017) can be seen in Figure 3. Most of the outstanding debt "today" was taken in 2005-2008 with significant shares of debt being concentrated in households our procedure identified as vulnerable. These shares are not negligible in the subsequent period as well, a fact whose significance we test in our probit specifications.

The results of the regressions testing for the significance of various mortgage characteristics are provided in Table 3b. We drop various socioeconomic characteristics, include equivalised household income and wealth and a dummy for debt installments as well as the urban area dummy. First two specifications are aimed at testing the significance that the period of the mortgage origination has in predicting household vulnerability. The results, as represented in these specifications, indicate that having assumed mortgage debt in the 2005-2008 significantly predicts vulnerability, implying a marginal effect of 18%. Third and fourth specifications test for the interest rate type, giving the result that the higher vulnerability may be associated with holding adjustable rates mortgages, implying a marginal effect of 24%. Finally, in the fifth and sixth specifications we find that holding a foreign currency denominated mortgage debt is associated with higher vulnerability, having a marginal effect at around 17,5% in this specification. It is important to stress that the varying size of the marginal effect of the debt installment dummy over the six specifications implies some collinearity with mortgage characteristics. While this means that the interpretation of the sizes of marginal effects of mortgage characteristics should be done with care, we are confident that the signs and the significance of the effects of mortgage characteristics are meaningful.

Since the adjustable rate and foreign currency denominated mortgages were predominant in the 2005-2008 period, we run additional regressions of mortgage characteristics, excluding mortgages taken in that period, leaving us with the sample of 414 households. The results are provided in Table 4, and indicate some significance for the foreign currency denominated mortgages (specification (5)), though only at 10%. Furthermore, adjustable rate mortgages are significant only after excluding the debt installment dummy from the specification (specifications (1) and (3)).

6. Conclusion

In this paper, we have provided a borrower based household level analysis of the factors possibly contributing to the vulnerability of indebted households' finances. In doing so, we have used information about debt burden indicators, given by DTA, DTI and DSTI ratios, available from the *Household Finance and Consumption Survey*, in order to identify vulnerable households. The latent class cluster analysis, done using the threshold values of the mentioned debt burden indicators, indicates that 14% of the households in our sample might be described as "vulnerable" in the sense that due to a significant debt and debt service amounts in comparison to the household's income and assets, it is either unlikely to be able to service its debt or it will be sufficiently difficult for the household to do so.

In order to examine which household characteristics may contribute to the fact that a household is vulnerable, we have used a limited dependent variable model of a probit type. In the regressions ran, we weren't able to find much influence of various socioeconomic characteristics of the household: the number of household members contributes "positively" to the probability of a household being vulnerable, while being outside of the labor force contributes "negatively". However, both of the variables are significant only on a 10% level.

Conversely, indebtedness characteristics of the household seem to be highly significant: households with mortgage debt have a much higher probability associated with being vulnerable. Furthermore, taking account of various mortgage characteristics we find that mortgages originated in the 2005-2008 period, adjustable rate mortgages as well as mortgages denominated in foreign currency tend to be highly predictive of the average household being vulnerable. For each of these characteristics, the variables constructed to reflect "counterfactuals", i.e. mortgages originating after 2008, fixed rate mortgages as well as domestic currency (HRK) denominated mortgages, are not significant in the provided specifications, providing some corroboration to our results. In order to partially "disentangle" the connection (i.e. correlation) between mortgage characteristics and the period of origination, we also ran a separate set of regressions excluding mortgages taken in the 2005-2008 period. We find some evidence (though less significant) that the particular mortgage characteristics, often associated with household credit risk in Croatia: adjustable rates and foreign currency denomination are somewhat associated with higher vulnerability.

Due to the correlation between various mortgage characteristics, caused by the high share of mortgages with these characteristics, it is difficult to isolate the influence of any of these by itself. Rather, we conclude that vulnerability is associated with mortgage debt either: through the *fact alone*, due to higher amounts of debt and debt service associated with mortgages, or through the specific mortgage characteristics often associated with higher household credit risk (adjustable rates, foreign currency denomination), or as an artefact of previous credit developments in Croatia, reflecting risk seeking behavior by either or both lenders and borrowers, particularly during the 2005-2008 period (Herceg & Šošić, 2011). To summarize, we believe our analysis provides an example how adjustable rate mortgages as well as mortgages denominated in foreign currency, typical of the 2000s period, coupled with lenient standards and increased borrowing based on optimistic expectations about future income, ultimately led to increased vulnerability for a non-negligible number of indebted households.

In light of our results, any macroprudential measure significantly tightening credit standards, or affecting interest rate type as well the currency of denomination should lead to a smaller number of households becoming vulnerable. However, additional insight is needed in order to be able to use household level data to inform macroprudential policymaking with more detail. In this respect, future research could be devoted to building a framework for stress testing of households as well as assessing the adequacy of various borrower-based macroprudential policy instruments in increasing household sector resilience in response to economic shocks (as well as other policy effects). Another strand could look towards enhancing the present research by extending the analysis to other European countries, once the whole wave 3 of the HFCS data set becomes available. Since the Croatian debt dynamics of the last 20 years is not unique, a possible future direction of our current research could consist of expanding the analysis to other countries which also experienced extensive credit activity as a part of their transition.

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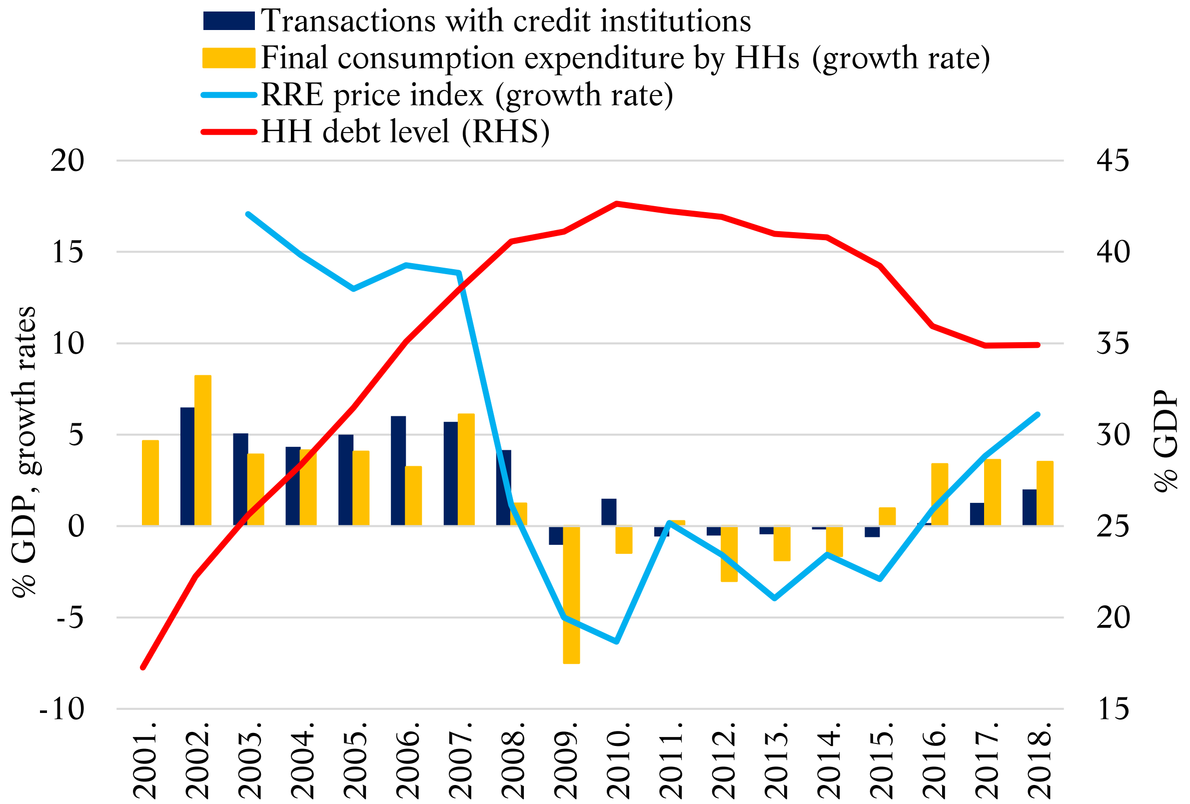
Appendix

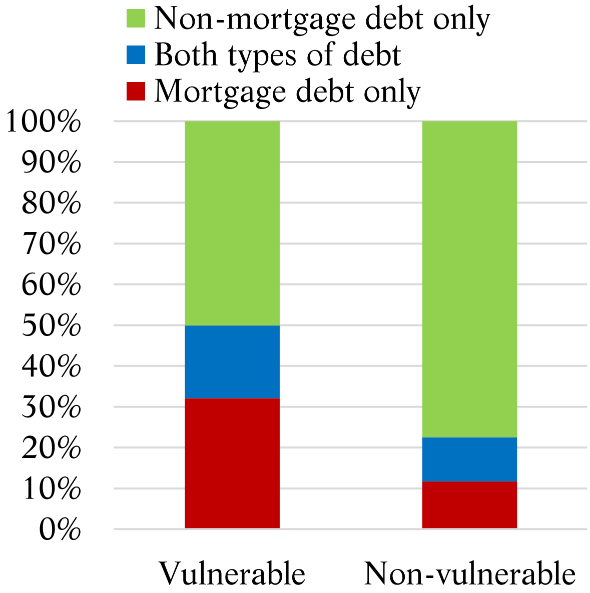
Figure 1 Credit dynamics in Croatia (2001-2018)



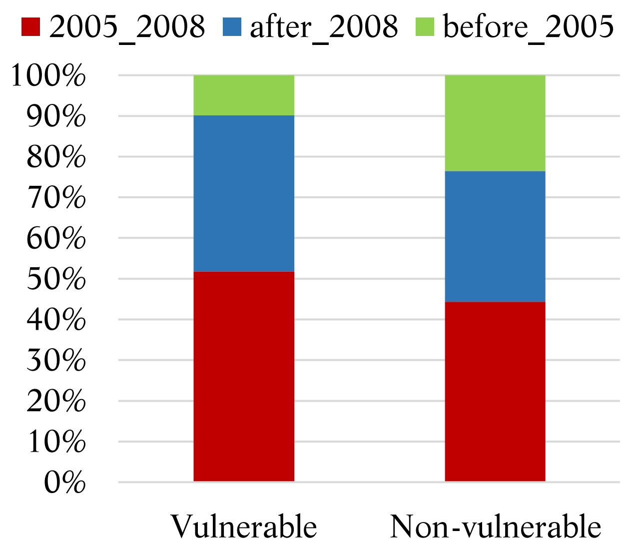
Note: Transactions with credit institutions exclude revaluations as well as other changes in volume.
Sources: Croatian Bureau of Statistics, Croatian National Bank

Figure 2 Indebtedness characteristics of vulnerable and non-vulnerable households

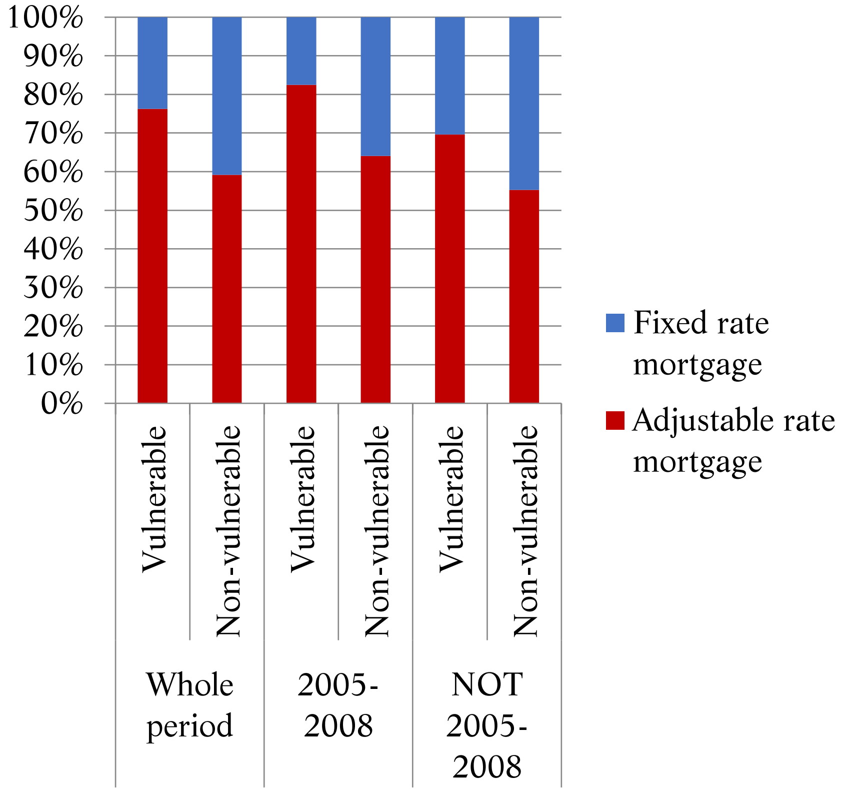
2a) with respect to the type of debt held



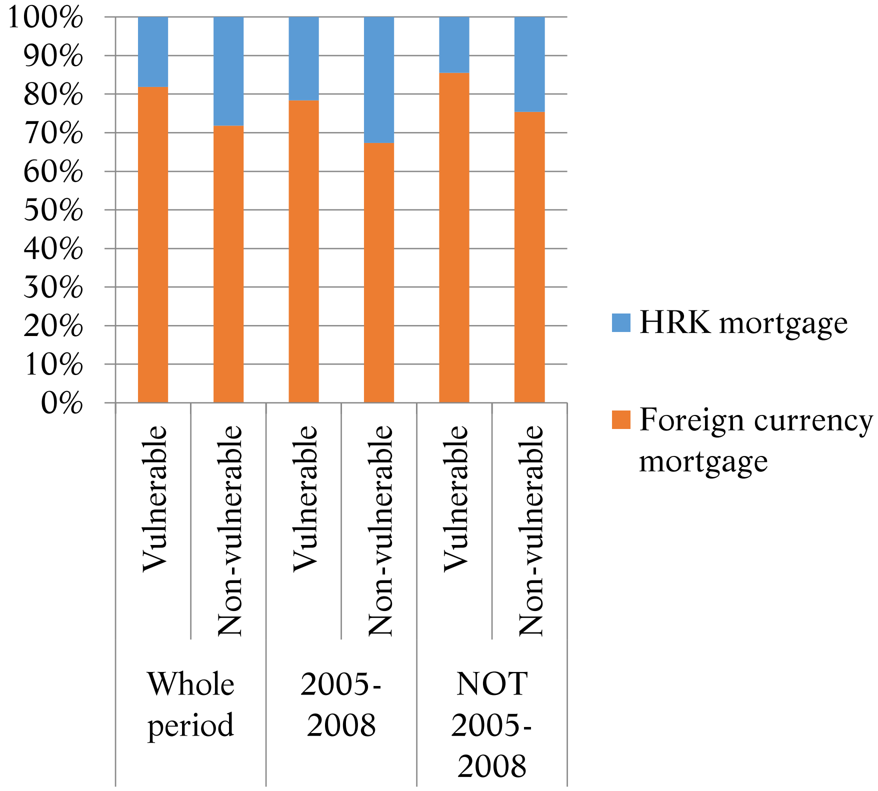
2b) with respect to the period of mortgage origination



2c) with respect to mortgage interest rate type and the period of mortgage origination

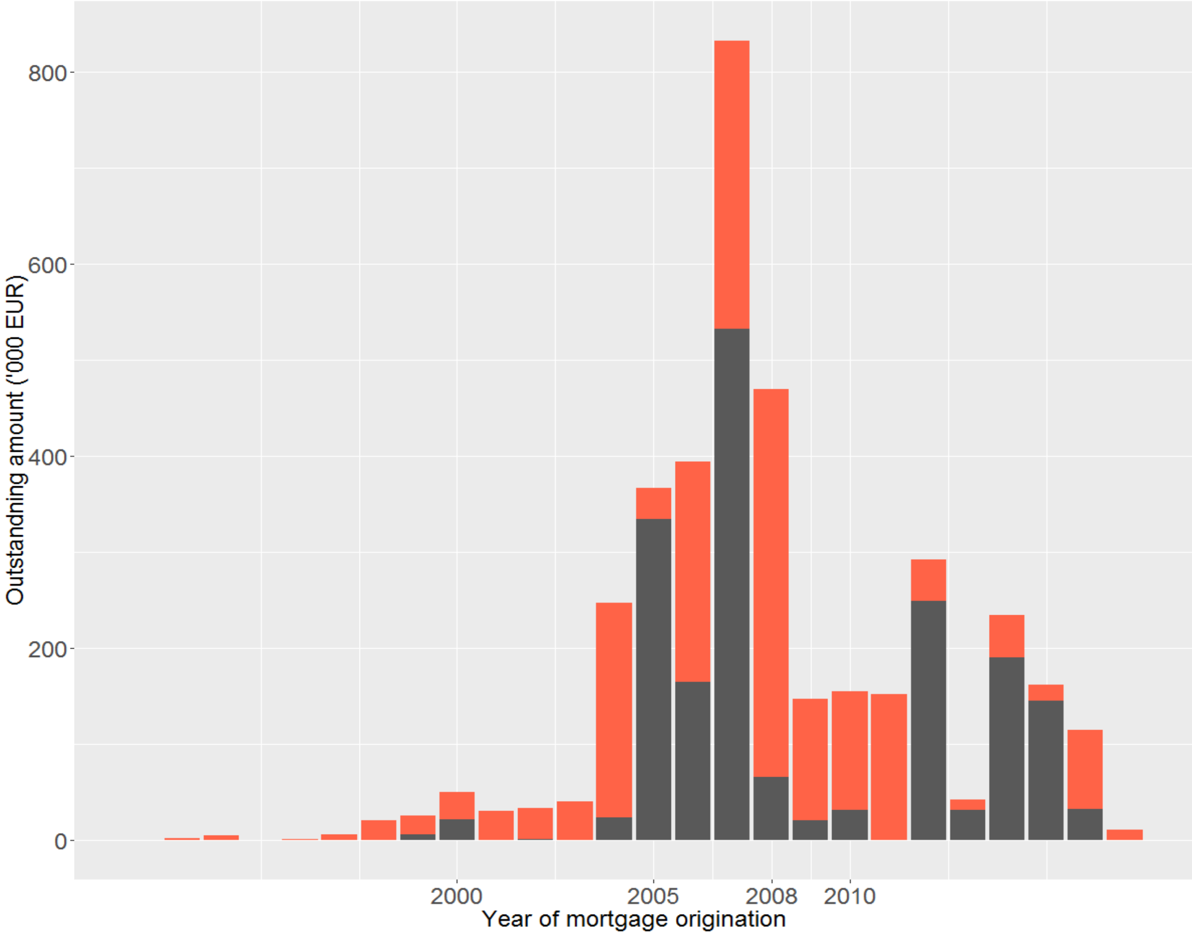


2d) with respect to the mortgage currency of denomination and the period of mortgage origination



Note: The figures show weighted distributions of the number of households. Figures 2b and 2c include households holding mortgage debt only.
Source: HFCS, authors' calculations

Figure 3 Distribution of outstanding mortgage debt with respect to the year of origination



Notes: The amounts are weighted; the shaded area represents the share of vulnerable households.
Source: HFCS, authors' calculations

Table 1 Characteristics of indebted households in Croatia with respect to vulnerability

Variable	Group	Distribution of vulnerable HHs	Distribution of non-vulnerable HHs
Household size	1 member	21,90%	9,64%
	2 members	29,94%	23,89%
	3 members	11,57%	24,92%
	4 members	24,13%	24,26%
	5+	12,46%	17,29%
Age of RP	16-34	9,06%	10,31%
	35-44	23,26%	31,11%
	45-54	22,05%	24,22%
	55-64	26,45%	21,42%
	65-74	10,68%	9,58%
	75+	8,50%	3,35%
Education of RP	Primary or none	0,75%	2,08%
	Secondary	67,91%	78,82%
	Tertiary	31,34%	19,09%
Employment status of the RP	Employee	55,06%	64,85%
	Self-employed	3,70%	4,48%
	Unemployed	7,84%	3,66%
	Retired	33,39%	26,60%
	Other	0,00%	0,42%
Income Quintiles	Lower 20%	56,14%	3,76%
	20% to 40%	10,56%	13,79%
	40% to 60%	19,83%	19,48%
	60% to 80%	8,44%	30,27%
	80% to 100%	5,03%	32,70%
Net Assets Quintiles	Lower 20%	25,24%	21,23%
	20% to 40%	17,03%	19,65%
	40% to 60%	17,29%	20,66%
	60% to 80%	26,56%	20,90%
	80% to 100%	13,87%	17,55%
Risk Attitude	No risk	72,17%	63,79%
	At least some risk	27,83%	36,21%
Residence	Rural	11,07%	27,77%
	Urban	88,93%	72,23%

Note: RP – Reference person, Source: HFCS, authors' calculations

Table 2 Results of latent class cluster analysis

	Probability of being above/below critical value (π_{jrk})							
Class:	DTA < 75%	DTA > 75%	DTI < 300%	DTI > 300%	DSTI < 40%	DSTI > 40%	TOTAL (p_r)	
Vulnerable	76%	24%	15%	85%	41%	59%	66,6	14%
Not vulnerable	93%	7%	100%	0%	98%	2%	401,4	86%

Table 3 Results of probit regressions – full sample

3a) Socio-economic characteristics

	(1)		(2)	
	ME	SE	ME	SE
Log(Income)	-11,1***	3,8	-11,3***	3,8
Log(Gross wealth)	0,7	1,3	0,7	1,3
Number of HH members (OECD scale)	4,2*	2,5	4,3*	2,4
Age of RP	0,0	0,2	-0,1	0,2
Gender of RP	-0,5	3,1	-0,4	3,0
Education RP: Tertiary	-2,1	3,8	-2,3	3,7
Labor status RP: Retired and other	-6,5*	3,6	-6,2*	3,5
Labor status RP: Unemployed	-1,5	7,2	-2,3	5,9
Has both types of debt	**20,7***	11,7		
Has only mortgage debt	**35,7*****	11,4		
Has mortgage debt			**24,9*****	7,3
Urban area	4,2	3,4	4,6	3,3
Riskattitude	-2,0	3,6	-2,4	3,6

Notes: The tables report marginal effects on the probability of a household being vulnerable evaluated at the means of independent variables and multiplied by 100. The number of household members is represented by the OECD scale: 1+ (additional Household members aged 14 or more -1)*0.5 + (Household members aged 13 or less)*0.3.
ME - Marginal Effects, SE - Standard Error, * p <.1; ** p <.05; *** p <.0.01

3b) Mortgage characteristics

	(1)		(2)		(3)		(4)		(5)		(6)	
	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE
Log(income equalized)	-10,5***	3,0	-10,7***	3,2	-10,4***	3,1	-11,0***	3,3	-10,6***	3,2	-11,0***	3,3
Log(gross wealth equalized)	0,5	1,2	0,7	1,4	0,3	1,1	0,9	1,5	0,4	1,2	0,8	1,5
Has debt instalments	11,0***	3,7	13,4***	3,8	8,6**	3,9	15,2***	4,1	9,4**	3,9	14,6***	3,9
Adjustable rate mortgage					**24,3*****	8,8						
Fixed rate mortgage							**-2,5**	6,7				
Mortgage taken in 2005-2008	**18,1****	8,3										
Mortgage taken after 2008			**8,5**	10,7								
Foreign currency mortgage									**17,4****	7,0		
HRK mortgage											**1,7**	9,7
Urban area dummy	4,3	3,1	5,3	3,5	5,2*	3,0	5,0	3,5	4,9	3,2	4,9	3,4

Notes: The tables report marginal effects on the probability of a household being vulnerable evaluated at the means of independent variables and multiplied by 100. Income and gross wealth are equivalized according to the OECD scale: 1 + (additional Household members aged 14 or more -1)*0.5 + (Household members aged 13 or less)*0.3.

ME - Marginal Effects, SE-Standard Error, * p <.1; ** p <.05; *** p <.0.01

Table 4 Results of probit regressions – excluding mortgages from the 2005-2008 period

	(1)		(2)		(3)		(4)		(5)		(6)	
	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE
Log(income equalized)	-7,7***	2,5	-7,8***	2,6	-7,6***	2,3	-7,5***	2,3	-7,5***	2,5	-8,0	N/A
Log(gross wealth equalized)	0,1	0,8	0,3	1,0	0,3	0,7	0,5	0,9	0,1	0,8	0,3	N/A
Has debt instalments	6,8**	3,5	8,8**	3,6					5,2	3,2	9,7	N/A
Adjustable rate mortgage	**14,8**	9,8			**23,4****	11,2						
Fixed rate mortgage			**3,0**	13,6			**9,5**	19,1				
Foreign currency mortgage									**17,5***	9,4		
HRK mortgage											**-3,7**	N/A
Urban area	4,2	2,6	3,9	2,7	4,9*	2,5	4,8*	2,6	3,4	2,5	3,6	N/A

Note: The algorithm for the specification (6) did not converge.