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Ivana Herceg and Vedran Šošić

The Anatomy of Household Debt Build Up: What Are the Implications for the Financial Stability in Croatia?

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1. Introduction

Rapid growth of Croatian household debt in period prior to the outbreak of the financial crises relaxed the financial constraint of the households, allowing them to frontload some of their consumption on expectations of rapidly growing incomes. However, at the same time it raised concerns about the potential implications of household over-indebtedness on stability of the financial system as economic outlook hugely deteriorated. The goal of this paper is to explore implications of the rapid debt accumulation by the households for financial stability[1].

Standard approach to this topic observes different macro-drivers of sharp household lending with special attention given to the EU integration process and real convergence. More recently, a consensus has started to form in the literature that the level of systemic risk in the financial sector depends on the actual distribution of debt (and assets) amongst the households rather than the aggregate level of indebtedness, prompting strong reliance of the field on micro data sources (Beck et. al., 2010 and World Bank, 2009). Such an approach ignores macroeconomic risks stemming from build up of external imbalances, but it is nevertheless an important extension of macro-prudential tools, such as early-warning indicators for sudden stops in capital flows or financial crises, in case those risks materialize.

This paper expands the range of the traditional micro-data analysis techniques as it aims to account for the changes in the distribution of household debt. First step in this direction is identification of the determinants of household debt over the observed period. However, instead of looking the main determinants of the amount owned by households at the mean of the distribution (estimated by the OLS), which is standard approach in the debt determinants literature, this paper employs a quantile regression analysis. The quantile regression (QR) allows for identification of the effect of different households' demographic and socioeconomic characteristics upon the total amount of debt across the whole distribution of the indebted households.

Since identification of the debt determinants is preformed on the non-random sample of only indebted households, the problem of the sample selection bias is likely to emerge. This problem could arise because some groups of households may be subject to financial constraint due to banks' lending policy or subjective perception of those policies. In order to control for the non-random bias, a modification of a two-stage Heckman model for the quantile regression proposed by Buchinsky (1998) was employed. According to this methodology unknown form of the sample selection bias term can be approximated following two-step procedure: first, the credit market participation selection parameter is estimated using distribution free semiparametric least squares estimation of single index (Ichimura, 1993), followed by a power series approximation of the bias term.

As a next step, changes in the characteristics of the indebted households will be used to disentangle their effects from the effects of changes in the estimated QR coefficients on the rise of total household debt during observed period. These characteristics are used to proxy for household creditworthiness and changes of estimated QR coefficients could be used to approximate possible relaxation of bank's lending standards and/or willingness of certain types of household to take more debt against their incomes. Decomposition method proposed by Machado and Mata (2005) will be employed in order to separate the effects of standard

[1] Conducted analysis and estimated results outlined in this paper are based on the study "Household Credit Risk in Croatia. An Analysis Based on the Households Budget Survey" (2009) carried out in collaboration of the Institute of Economics, Zagreb and Croatian National Bank.

relaxation vs. household characteristics on the debt distribution. This technique extends the traditional Oaxaca decomposition of these effects on mean (Oaxaca, 1973) to the entire distribution. A special attention will be given to the households carrying the highest amounts of debt.

The paper is organized as follows. Section 2 gives an overview of the related literature and presents the motivation for the analysis outlined in the rest of the paper. Section 3 describes the methodology used in estimation of household debt determinants and decomposition of its growth from 2005 to 2008. Section 3 describes the used dataset and expected effect of different households' characteristics on their decision to take bank loan. Empirical results of the selection and outcome equation of the sample selection model together with decomposition of household debt growth are given in section 5. Section 6 concludes.

2. Literature review: Household lending and financial (in)stability

Levels, dynamics and quality of household lending have not traditionally been subject of researchers seeking to identify causes of banking system distress. Households were considered to be a trustworthy borrower that repaid its debts in time, or at least had sufficient collateral to prevent excessive bank losses on household lending. Thus, episodes of deterioration in quality of loans that closely followed recessions have historically mostly been confined to the corporate sector. In that vein Caprio (1998) noted that "a financial crisis usually involves a corporate debt problem in the non-bank financial sector".

Such a benign perception of household lending became increasingly scrutinized since the late 1990's, as the run-up in household debt accelerated, and eventually dissolved with the advent of the sub-prime crises. Most advanced countries experienced a synchronized growth in household indebtedness over the previous decade. The extent and composition of the household debt increase differed from one country to the next, but very few of them managed to avert the general trend of rapid debt build-up. In parallel with growing indebtedness, during the late 1990's and especially over the previous decade, a growing literature on household borrowing started to emerge (Girouard et al., 2006). In that sense, some researchers' fascination with household borrowing prompted by the rapid growth of household indebtedness and household leverage is a rather novel phenomenon.

Most of the papers on household lending published in this period could be classified in several lines of research. Many of the papers adopted a “macro” approach as they employed aggregate economic data in dealing with causes of a widespread growth in household indebtedness. Authors using this approach identified a range of different factors that accounted for the observed dynamics of household debt, such as combination of favorable financial conditions related to benign monetary policy, buoyant housing markets and now notorious innovations in credit markets that have eased the access to credit for lower-income borrowers and reduced financial constraints for first-time homebuyers (see Girouard et al., 2006; Dynan and Kohn, 2007; and Dynan, 2009).

Papers adopting a “macro” approach also dealt with consequences of growing household indebtedness. However, observing aggregate household balance sheets and aggregate data on debt service burdens provides a very rough guidance on actual household vulnerabilities as it conceals potential major differences between groups of households. As this paper explores another avenue, rather than providing a comprehensive overview of the issues and methods used in this literature, only some major conclusion of papers dealing with Central and Eastern European countries will be briefly addressed.

Central and Eastern European countries have featured prominently in this area of research because of rapid lending growth driven by rapid economic development, financial liberalization and opening as well as convergence of their financial systems towards structures found in Western economies. Croatia had a bit of special position because of relatively high level of indebtedness already in mid-2000's, structure of bank borrowing that was early tilted towards household debt and slightly slower recent growth of household indebtedness than that found in most Central and Eastern European countries. Still, Croatian household indebtedness more than doubled in the period between 2005 and 2008 and, given the fairly high initial level, brought it to the top amongst Central and Eastern European countries, next only to some of the Baltic Republics. Aggregate household debt therefore converged to the average EU level (see Figure 1) as it reached 40.5% of GDP by the end of 2008.

This debt growth relaxed the financial constraint of the households, allowing them to frontload some of their consumption on expectations of rapidly growing incomes (in line with life-cycle permanent income hypothesis), but at the same time it raised some concerns about the potential implications of household over-indebtedness on stability of the financial system, especially after the economic outlook hugely deteriorated. However, most of the papers addressing lending expansion before the ongoing crises attributed it to equilibrating forces of liberalization, convergence and alignment with the EU structures. Mihaljek (2006) noted that "for the time being, the expansion of private sector credit has been mostly a benign phenomenon". Kiss et al. (2006) agreed "that large part of the credit growth in new member states can be explained by the catching-up process, and, in general, credit/GDP ratios are below the levels consistent with macroeconomic fundamentals". Kraft (2006) is interesting because of focus on household lending in Croatia. However, his conclusion seems similar as he attributed it to "strong performance in banking sector reform and in maintaining low inflation" while leaving "weaknesses in enterprise reform and privatization". Šonje (2009) even after the onset of the crises remarks that path of credit integration looks remarkably similar in most Central and Eastern European countries to earlier episodes of financial integration and that credit growth in very few countries extends beyond justifiable on those grounds. Zdzienicka (2010) is one of a few counter-examples reporting indications of "excessive" credit developments in most Central and Eastern European countries until 2007, and even since for some countries. Obviously very few of the researchers found some reasons for concern in general rapid lending growth based on the "macro" approach.

The second major research agenda adopted a "micro" approach that was much more intimately intertwined with the actual patterns of the household debt expansion. Papers in this category predominantly use data on individual households compiled from various household surveys, allowing them to identify the precise profile of household vulnerabilities, in contrast to "macro" approach, where such information remains unknown. Despite recent advances, as recently as 2004 Brown et al. noted that "research into the determinants of individual debt or household level debt is surprisingly scarce".

Research on the profile of household borrowing from the "micro" perspective looked for "deeper" causes of debt accumulation by testing if rising debt resulted from optimizing, welfare enhancing behavior of the households under more favorable financing conditions. In a way, distinguishing whether households use easing of liquidity constraint in order to align their spending profiles with the optimal or market imperfections, such as short-sightedness, behavioral inertia or excessive risk-taking, actually increase the volatility of household expenditures by making household spending decisions intrinsically unsustainable under constant shocks developed into the major undertaking of this literature. Life-cycle permanent income hypothesis[2] became the standard workhorse of the literature as researchers strived to guess the extent to which the relaxation of the households' financial constraint improved the way they smooth their consumption over time. This also brought focus on the actual distribution of debt across households and the way it interacts with the household characteristics to produce patterns of over-indebtedness and financial distress.

Different unanticipated shocks, such as those to income, interest rates or exchange rate, have a potential to raise present value of household debt above present value of its assets and make optimal spending patterns unsustainable, which is one of the ways to define the problem of financial distress. Even if the concept over indebtedness occurred in this line of literature, it was confined to a byproduct of unavoidable fundamental uncertainty rather than systemic faults related to ever-easing financing constraint. Thus, it is not surprising to see papers written in this spirit reporting that over indebtedness patterns had more to do with idiosyncratic shocks households faced than any systematic income, age or family structure factors, while households in countries with deeper financial systems were no more prone to over-indebtedness (see Betti et al., 2007, Beck et al., 2010).

Possibility to frontload some of the household consumption on expectations of growing future incomes also raised concerns about the potential implications of household over-indebtedness. These concerns about potential consequences of household indebtedness led to another strain of the literature with much more straightforward view of risks stemming from rising household debt. Relaxation of the borrowing constraint mitigates liquidity restrictions and allows households to increase spending, while reducing their "savings buffer" (and consequently their aggregate savings rate[3]) as households feel they could use lending rather than own precautionary savings to insure against shocks to their consumption. But a combination of reduced savings buffers and high debt burden also makes households more susceptible to unanticipated shocks that lead to over-indebtedness and financial distress. Mian and Sufi (2009) clearly show the link between stronger growth of loans to less creditworthy customers (measured by their FICO credit score) and subsequent rise in the number of loan defaults in US regions. Identification of possible myopic behavior also opened doors to policy advice. Brown et al. (2004) reported a major impact of optimistic financial expectations on the level of household debt in the UK and highlighted the importance of curbing unwarranted financial optimism for avoidance of excessive debt problems.

Many of the field practitioners, who filled much of the gap left by academic economists in addressing household financial vulnerabilities, didn't care whether financial distress was caused by household myopia or unforeseen events. Split in the literature between those who saw rising debt as a sign of ability of households to better align their spending patterns with optimizing behavior within the framework of inter-temporal budget constraint and those who emphasized potential risks related of excessive indebtedness due to macroeconomic fluctuations and myopic borrowers didn't impress many of those who looked for implications of rising debt on household vulnerability. Leaving theoretical considerations aside allowed focus on the response of over-indebtedness on different kinds of shocks. "Practitioners"

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[2] For more on the life-cycle permanent income hypothesis see Crook (2006) and Del-Rio and Young (2005).

[3] Goh (2005) uses New Zealand as an example to emphasize macroeconomic consequences as higher household debt and lower savings also increase external vulnerability of the whole country, but such implications of rising household debt ate beyond the scope of this paper.

focused on problem of over-indebtedness from various perspectives, such as social implications of the change in the number of persons exposed to cycle of ever-increasing debts (Brown et al., 2005) implications of non-payments arising from household financial distress on the stability of financial system (Herrala and Kauko, 2007) or the way rising household debt interacts with population ageing to produce specific patterns of vulnerability.

Methodological approaches used to tackle the problem of over indebtedness if one of the touching points between those seeking fundamental forces shaping indebtedness patterns and practitioners looking at impact of shocks on financial distress. Still, availability of data on individual households didn’t allow for resolving in a satisfactory way the subtle line which denotes the transition of a household into over-indebtedness. There are three main methodological approaches to the definition of financial distress in the literature on household indebtedness, with occasional resort to some additional, ad hoc definitions, although different variations of those approaches make the actual number of criteria used in the literature much larger (see Betti et al., 2007, Beck et al., 2010 for more detailed explanations on some of those measures). Also, actual underlying structure of the data source used, such as survey design, also influence the exact definition of the vulnerability criteria used and make harder comparisons over countries and different.

First approach, which observes so-called "objective" measures of household financial distress, is based on the idea that households are vulnerable in case their indebtedness or debt service ratios exceed a certain threshold. Sometimes indicators of household consumption relative to income are used rather than debt/repayment ratios, with high consumption being an indicator of possible financial distress (Betti et al. 2007). This approach is routinely used by researchers and has a natural appeal to field practitioners interested in financial distress, such as commercial and central banks (see Unicredit, 2009 and European Central Bank, 2007). Ratios of debt to income in the range of 450%-600% and debt repayment to income of 30% are commonly used as thresholds of vulnerability. However, this indicator also suffers from several serious deficiencies. First, although most empirical studies use similar ratios, there are no established thresholds that unavoidably lead to household financial distress. Further on, it compares ratios of debt and repayments to actual income rather than lifetime income, while households may be inclined to run debt exactly at times when their current income declines below their earning potential.

The concept of so-called "financial margin" is a derivative of the "objective" approach which lessens some of the problems arising from the use of arbitrary margins and has gained much popularity among the practitioners simulating impacts of various shocks on the ranks of vulnerable households. Financial margin refers to income reserve that remains after debt service and household-specific poverty line have been subtracted from the household income. Households with negative financial margin are usually considered to be vulnerable. However, calculation of household specific "financial margin" still does not resolve the problem of setting an arbitrary threshold by a researcher but rather designates it to the institution setting poverty lines.

The second approach is a "subjective" in a sense that it relies on a subjective evaluation of household balance sheets and debt servicing burden. Typically, these measures are based on the number of households reporting a degree of hardship in servicing its debt. One of the problems with this indicator is that subjective well-being does not necessarily have to correlate closely with income, but may be influenced by other factors, such as comparisons with the reference group (Georgarakos et al., 2009).

The final approach is co called "administrative" where data on actual bankruptcies or debt defaults is used. As most studies use household survey data, a derivation of this approach uses self-reported debt arrears as an indicator of financial distress. Sometimes the concept of arrears is expanded to include not only arrears incurred towards financial institutions, but also late payments of certain utilities or other bills such as rent. Also, it is possible to vary thresholds for arrears from one to several months in order to make the criteria more or less stringent or align it with actual banking practices. This definition is the one that is most closely aligned with the concept of bank losses stemming from household financial distress, although the fact that data a collected with the households introduces some differences.

While "micro" approaches greatly differ in their methodologies with respect to the actual measure of "distress" used, there is hardly any advice on the way how to identify financially distressed households for different purposes. It is therefore not surprising to find that all these indicators in countless variations are interchangeably used in studies of different phenomena.

Most "micro" studies of risks arising from household lending conclude that risks for the financial system are negligible. Conclusions from a sample of studies performed in different countries look almost exactly the same. Beer and Schürz (2007) assert that "the risks associated with private debt that could threaten financial stability in Austria are minimal." Fuenzalida and Ruiz-Tagle (2009) simulate impact of unemployment on the Chilean financial system and conclude that even higher levels of unemployment do not necessarily imply that the financial system will suffer a significant default shock by households. Herrala and Kauko (2007) are a bit more cautious in their simulations of risks related to household lending in Finland as they warn that "In most states of the economy household loans bear a relatively low credit risk to banks. However, under extreme conditions with a coincidence of large and persistent adverse shocks to unemployment, interest rates and housing prices, even household loans could become a threat to financial stability." Keese (2009) in his study on Germany does not particularly emphasize macroeconomic shocks as he finds that "trigger events such as strokes of fate (death, separation, or divorce), change in household composition (cohabitation or marriage), unemployment, and childbirth account for most changes in the debt situation of a household."

For Central and Eastern European countries Beck et al. (2010) called for greater use of micro data to assess household indebtedness and overall financial stability as they note that "To date, little is known about the incidence of household indebtedness and its distribution". There are, however, a few studies with very similar findings to those in the "Western" literature. Holló and Papp (2007) conclude that the capital adequacy ratio of the Hungarian banking system would not fall below the current regulatory minimum of 8 per cent even if the most extreme stress scenarios were to occur. Żochowski and Zajączkowski (2006) for Poland conclude that none of the risks they analyzed is important enough to pose a threat to the financial system stability. In a more recent study Daras and Tyrowicz (2009) find that "even small changes in the employment persistence or unemployment risk can lead to considerable deterioration of households' liquidity and therefore the financial stability of the whole mortgage market", but this finding is obtained by employing a rather soft definition of financially distressed households which is much higher that non-performing loans even before the application of the stress scenarios.WB (2010) is also much more cautious from the rest of the mentioned studies as they that report "results of stress tests on household indebtedness in selected countries suggest that ongoing macroeconomic shocks may significantly expand the pool of households that will be unable to meet debt service obligations. Interest rate shocks in

Estonia, Lithuania, and Hungary, for example, increase the share of vulnerable households or borrowers at risk (in percent of all indebted households) by up to 20 percentage points, depending on the magnitude and severity of the shock."

While there are several potential explanations for rather favorable results of most stress-testing exercises performed for the household sector in Central and Eastern European countries, such as mild scenarios, part of the explanation could probably be attributed to the selection of vulnerability indicators used. For now there are no in-debt examinations of their properties, but casual observation of different vulnerability indicators calculated on the basis of the Croatian data reveals several interesting features. First, as can be seen from the Table 1, there are wide variations in the levels of vulnerable households on the basis of different criteria. Moreover, there is very little overlap in presented indicators so all of the indicators together cover a large portion of all households, in excess of 40% for some combinations, while there are a few vulnerable households according to multiple criteria. Further on, although there has not been much dynamics during the observed period, indicators have often moved out of line with each other. Because it is obvious that conclusions of studies on household distress critically depend on the properties of the indicators used, of which very little is known, this paper in goes some way back to observation of changes in debt determinants and debt distribution.

3. Methodology

In order to capture in full the effects of the rising household indebtedness on the financial stability, it is important to account for the changes in the whole distribution of household debt. Literature on household debt determinants is in that respect a natural starting point. However, papers prepared in this tradition usually rely on standard OLS regression (Del-Rio and Young, 2005) or Tobit model (Magri, 2002 and Crook, 2006) that identifies the determinants of the amount owned by households at the mean of the distribution, thereby ignoring the effects at the debt distribution tails which may be the most important from the financial stability point of view. As Figure 2 indicates, during observed period the Croatian household debt distribution moved in line with the aggregate level of household indebtedness, as can be seen from the right-side shift of the whole distribution of household debt. However it became asymmetric, indicating a possible increase in the ranks of vulnerable household. For these reasons we employ the quantile regression (QR) analysis that allows for identification of the effect of different households' demographic and socioeconomic characteristics upon the total amount of debt across the whole distribution of the indebted households.

The quantile regression model was first introduced by Koenker and Bassett (1978). It can be viewed as a location model in which quantiles of the conditional distribution of the response variable (log credit in our application) are expressed as a function of the observed covariates (Koenker and Hallock, 2001). It is assumed that the conditional quantile of the response variable is linear in covariates (Buchinsky, 1998a), i.e.

$$Quant_\theta(y_i / x_i) = x_i^{'}\beta(\theta), \text{ where } Quant_\theta(u(\theta)/ x_i) = 0 \text{ and } \theta \in [0,1] \qquad (1)$$

The coefficient vector $\beta(\theta)$ is estimated as a solution to minimization problem where absolute errors are asymmetrically weighted with weight θ on positive errors and weight $(1-\theta)$ on negative errors (Kuan, 2007):

$$\min \frac{1}{n}\left\{ \sum_{i:y_i \geq x_i'\beta(\theta)} \theta \left| y_i - x_i'\beta(\theta) \right| + \sum_{i:y_i < x_i'\beta(\theta)} (1-\theta)\left| y_i - x_i'\beta(\theta) \right| \right\} \tag{2}$$

The amount of the loans is observable only for those households who are actually indebted. Therefore the selection of the indebted households in the sample is not random because it is determined by household's decision to apply for a loan and bank's decision to approve the loan. Both decision processes are based on the evaluation of households' socio-economic and demographic characteristics. Since identification of the debt determinants is preformed on the non-random sample of only indebted households, the problem of the sample selection bias is likely to emerge. Also correlation between the household's decision to participate in the credit market and the amount of the bank loan, could give rise to this selectivity bias. At the end such bias caused by inadequate sample selection can influence the outcome results of our analysis[4].

Standard sample selection model which allows for sample selection bias correction is given by (Schafgans, 1998):

$$\begin{aligned} &Y_i^*(\theta) = \beta_o(\theta) + X_i\beta(\theta) + \varepsilon_i, \quad \theta \in [0,1] \\ &D_i = I(Z_i\gamma + e_i > 0) \quad \textit{and} \\ &Y_i = Y_i^* D_i \quad \textit{for} \quad i = 1,\dots,n \end{aligned} \tag{3}$$

where (Y_i, D_i, X_i, Z_i) are observed random variables and $I(\cdot)$ is the indicator function. The first equation in the model is usually referred to as an outcome equation and the second equation is the selection equation. In our analysis Y_i^* represents the possible amount of debt that each household in the sample of all households would carry dependent on its characteristics and D_i is dummy variable indicating whether the individual household is in fact indebted or not. Therefore the observed amount of loan for household i is given by Y_i. Characteristics influencing the household's decision to apply for a loan, i.e. bank's decision to grant the loan are given by Z_i and the determinants of the amount of loan are given by X_i, where X_i variables are a subset of the Z_i variables.

The standard approach to the estimation of the represented sample selection model is the Heckman's two-step procedure[5] according to which first a probit regression is estimated on the decision to participate on the credit market. Probit results are then used to compute the inverse Mill's ratio. Finally, an ordinary least squares regression is applied to the amount of loan, where in addition to the explanatory variables the inverse Mill's ratio is included. This approach assumes that (ε_i, e_i) are bivariate normally distributed, independent of (X_i, Z_i) with zero mean and unknown covariance matrix (Schafgans, 1998).

However, deviations from the normality assumption can lead to inconsistent and biased estimator (Schafagans, 1998) In order to control for the non-random bias, a modification of a two-stage Heckman model for the quantile regression proposed by Buchinsky (1998b) is

[4] For more on the econometric implications of sample selection bias see Heckman (1979).
[5] For more see Heckman (1976).

employed. According to this method, a conditional quantile of the observed amount of household credit depends on, apart from the household's specific characteristics, a bias term of the unknown form (Buchinsky, 1998b). Following Buchinsky (1998b) and Albrecht et al. (2008) we estimate:

$$Quant_{\theta}\left(y_i / Z_i = z_i\right) = x_i \hat{\beta}(\theta) + h(\theta)(z_i \gamma); \;\; \theta \in [0,1] \tag{4}$$

The vector X consists of the observed socioeconomic and demographic characteristics of households that carry debt. Apart from the covariates included in X, vector Z contains at least one additional variable that influences the probability of household's participation in the credit market, but which must be uncorrelated with the amount of the debt. In our case, residence in rural areas is used as a proxy of higher costs related to obtaining loans due to low density of banking branches, while investments in life insurance schemes is used as sign of financial sophistication, both of which standard in the literature of debt determinants (Margi, 2002 and Ruiz-Tagle and Vella, 2010). The sample selection correction term $h_{\theta}(z_i \gamma)$ is of the unknown form, quantile specific and doesn't assume normality. In order to approximate the function $h_{\theta}(z_i \gamma)$ we adopt a two-step procedure proposed by Buchinsky (1998b). First the credit market participation selection parameter γ is estimated using distribution free semiparametric least squares estimation of single index model introduced by Ichimura (1993) on the whole sample of households. Afterwards, the bias term $h_{\theta}(z_i \gamma)$ is approximated by a power series expansion as suggested by Buchinsky (1998b) and Newey (2008)[6],

$$\hat{h}(\theta)(z_i \gamma) = \sum_{l=0}^{\infty} \delta_l(\theta) \lambda(z_i \gamma)^l \tag{5}$$

where $\lambda(\cdot)$ represents the transformation of the single index $(z_i \gamma)$[7]. We continue estimation with the single index representation, $\lambda(z_i \gamma) = z_i \hat{\gamma}$. Finally, the vector $\hat{\delta}_l(\theta)$ is obtained together with the coefficient vector $\hat{\beta}_i$ from the quantile regression of the log credit on the covariates (x_i) and the approximation of the bias term $\hat{h}(\theta)(z_i \gamma)$[8].

As households differ in their characteristics, it is necessary to control for changes in the creditworthiness of the indebted households in order to capture the possible negative effects of the rising household debt on the financial stability. To achieve that, in the second step of our analysis changes in the characteristics of the indebted households at different quantiles of debt distribution will be used in order to disentangle their effects from the effects of changes in the estimated QR coefficients on the rise of total household debt during observed period. Households' specific socioeconomic and demographic characteristics are used to proxy for household creditworthiness and estimated QR coefficients approximate the possible relaxation of bank's lending standards and/or willingness of certain types of household to take more debt

[6] In our study bias term was approximated by polynomial of order 5.

[7] Any function of the $(z_i \gamma)$ can be used, including the single index. For more see Newey (2008) and Buchinsky (1998b).

[8] However, the intercept in the equation (4) is not identified since it is difficult to separate the intercept $\hat{\beta}_0$ from the first term in the power series approximation of the selection equation $\hat{\delta}_0$. For more on estimation of the intercept in sample selection model see Andrews and Schafgans (1996).

against their incomes. Decomposition method proposed by Machado and Mata (2005) will be employed in order to separate the effects of standard relaxation vs. household characteristics on the debt distribution. This technique extends the traditional Oaxaca-Blinder decomposition of these effects on mean (Oaxaca, 1973) to the entire distribution. The Machado-Mata decomposition is widely used in the literature on wage inequality for which it is primarily developed[9]. As far as authors are aware, it has never been used to analyze changes in the patterns of household debt. In order to approximate the implicit scoring models of the banks two counterfactual marginal credit densities are generated: a marginal density function of the log credit that would prevail in the 2008 if the households' characteristics were the same as in 2005 and a marginal density function of the log credit that would arise in 2008 if the "returns" to households' characteristics in 2008, i.e. implicit scoring models of banks, were the same as in 2005.

$$X^{08}\beta_{\theta}^{08} - X^{05}\beta_{\theta}^{05} = X^{05}\left(\beta_{\theta}^{08} - \beta_{\theta}^{05}\right) + \left(X^{08} - X^{05}\right)\beta_{\theta}^{08} + residual \qquad (6)$$

This decomposition allows us to approximate the contribution of the banks' evaluation of the household's characteristics in the process of the loan approval (the first term in (6)) from the contribution of the improvement of the household's creditworthiness in period between 2005 and 2008 (the second term in (6)) to the observed growth of the household debt. Residual represent the part of household debt change unaccounted for by the estimation method. In the same way the contribution of the individual household characteristic to rising indebtedness can be measured.

4. Data

In our analysis we use micro data from the Households budget survey (HBS). Since 1998 Central Bureau of Statistics has been annually conducting HBS on the random sample of private households[10] in Croatia. The data on income, wealth and most household consumption expenditures is collected continuously during 12 months period with changing surveyed sub-sample of private households every two weeks. There is no panel part of the sample[11]. Since appropriate weight is assigned to every surveyed household, i.e. the number of households in the population that surveyed household represents, calculation of aggregate estimates for population is enabled. Apart from the household-level data on income and expenditures, HBS gives insight into socioeconomic and demographic characteristics of surveyed individuals, allowing for analysis of indebtedness of households according to the disposable income brackets and different characteristics of households' head. This advantage of HBS and other micro data sources is important for the household indebtedness analysis since debt incident is not equally distributed amongst households of different age, sex, education or area of residence[12].

[9] See Machado and Mata (2005), Albrecht and Bjorklund (2003), Albrech et al. (2008), Nestić (2010) etc employ it in order to decompose gender wage differential.

[10] Household is every family or other community of individuals who live together of spend their income together for covering the basic existential needs. Household is also every person who lives alone (CBS, 2010).

[11] The sample frame used for selection of dwellings occupied by private households in 2008 was based on the Census 2001 data.

[12] For more details on HBS see CBS, 2010.

Apart from obvious advantages that data from household-level surveys have in relation to macro data, there are also several disadvantages that should be kept in mind. The biggest drawback of most surveys is undervaluation of household disposable income and debt (Daras and Tyrowicz, 2009). Lower level of aggregate household income and bank loans compared to macro data also appears in HBS, due to significant distrust and unwillingness of households to completely and correctly reveal the sources, values and structure of their income and debt and also possibly poorly representative sample in respect to the high income households. Compared to available macro data, aggregate household disposable income from HBS is on average 27% lower during the observed period. However, the aggregate household debt is also unevaluated for some 46% so deviation of different measures of relative household indebtedness can be tolerated.

For the purpose of our households indebtedness research we use HBS for years 2005 and 2008, fairly recent period during which a continuous expansion of household debt took place. Before employing the proposed analytical framework the sample was cleaned from identified errors and omissions and households that choose not to answer and/or didn't know the answer to the questions about the level of their disposable income and/or the amount of debt owned were removed from the sample[13].In order not to further reduce the sample size, for several identified households with only one lacking data in data matrix, the missing value was replaced with the explanatory variable's mean[14]. The estimation of the probability of household holding debt (sample selection equation) was performed on the whole sample of households, while identification of the determinants of the amount of debt owed (outcome quantile regression equation) was based on the sub-sample of indebted households[15] regardless of the type of their loan. The dependant variable in selection equation is a binary variable that equals 1 if household has some type of bank loan and 0 if not. The second dependant variable in output equation is natural logarithm of the observed total amount of household's loans. A special attention will be given to the households carrying the highest amounts of debt in order to monitor changes in their determinants of indebtedness as well as changes in the resulting concentration of household debt during the observed period[16].

In Table 2 some descriptive statistics for the key variables is given for the whole sample of surveyed households in two observed years and three sub-samples: households with no loan, households with some type of bank loan and households with bank loan taken during the last year.

In both of the observed years around 32% of surveyed households had some type of bank loan, although some mild rise of the proportion of indebted households can be observed during this period. Strong growth of Croatian economy during observed period gave boost to the rise of households' disposable income and facilitated satisfying down-payment conditions as well as giving rise to optimistic expectations, thereby increasing demand for loans. At the same time, rising competition in the banking sector lowered interest rates and non-price lending standards of banks. From Table 2 it is evident that households with debt liabilities in 2005 had around 21% higher disposable income per household member than households with no bank loan. However, this difference between indebted households and those without any debt was significantly reduced over the same period, indicating that loan expansion took place

[13] The whole sample size for 2005 and 2008 is 2651 and 3010.

[14] In years 2005 and 2008 these households account for 0.26% and 0.20% of all households in the sample. In the sub-sample of indebted households they make 0.83% and 0.60%, respectively.

[15] The sample size of indebted households for 2005and 2008 is 845 and 1003, respectively.

[16] In the observed years the two highest deciles account on average for 56% of the total household debt.

amongst less creditworthy households. At the same time, easier access to the loan market and cheaper borrowing is reflected in the steep rise of the average value of new loans in comparison to the average household disposable income during this period, which is a signal of rising vulnerabilities.

Apart from level of disposable income, participation in the credit market and the amount of debt is also positively correlated to the level of education of household's head since majority of households with some type of bank loan in both observed years have middle or high level of education while around 45% of households with no debt liabilities haven't even finished high school. Level of education reflects the potential for future income growth, but it also implies easier collection and evaluation of information needed before deciding whether to apply for a loan or not (Magri, 2002).

Age of the household head is another important factor in explaining credit market participation. As suggested by the life-cycle permanent income hypothesis, young households with expectations of rapidly growing incomes and high marginal utility of consumption are more likely to demand debt (Crook, 2005). After certain age threshold debt incident and the amount borrowed is expected to decrease as household need for satisfying basic living conditions and expenditures diminishes. Table 2 shows that households carrying debt are on average around 9 years younger than households with no debt. In both observed years percentage of indebted households grows with age of the household's head with slightly more than 55% of all indebted households aged between 40 and 59 years, after which debt incident decreases.

Being married and having big family also increases probability of having a debt, as larger families especially with young children usually have higher living expenses. Households whose head is working are more likely to have a bank loan, especially if he is employed in the public or private company engaged in tertiary activity and has permanent employment contract with full working time. Men are usually reported as a household head in he HBS, but those households are disproportionably more likely to have debt liabilities. The area of residence is another factor affecting the decision to apply for a loan. In the whole sample almost 50% of households live in rural areas. This percentage is even higher for households that don't have debt, whereas those that do are more likely to be living in towns and cities. This could be the consequence of density of bank in less populated rural area but also poor educational profile of population living in such municipalities which rises entry cost in the debt market. Households investing in life insurance are probably more financially literate and in probably better positioned to apply for a loan, but also some types of bank loans, especially residential loans, are also likely to be collateralized by life insurance contract, making it useful in identification of wheatear or not household carries debt. As HBS data shows, life insurance is much more present in the sub-sample of households with some type of bank loan than in the sub-sample of households with no debt.

5. Estimated results

5.1. Results of the selection equation and the outcome equation

The empirical semiparametric least square (SLS) estimates of the selection equation are presented in Table 3. Most explanatory variables take the form of dummy variables rather than continuous variables. Therefore, presented estimation is referenced to baseline household whose head is a married male, aged between 50 and 59 years, working permanently, full-time hour in a private company dealing in tertiary activity. He owns and lives in a real-estate in urban area without housing loan liabilities and doesn't have life insurance. Estimated parameters are identified up to an unknown scale, so all coefficients are normalized relative to the value of the coefficient of the only continuous explanatory variable, logarithm of household's disposable income.

Although most identifying variables have very similar effects on the probability of household having bank loan in both observed years, the effect of some explanatory variables changed during observed period. As expected, household's disposable income has positive impact on the household's participation in credit market in both years. Even though theory suggests that probability of having bank loan should decrease with rising current income (Magri, 2002), the obtained estimates could indicate that indebted households in our sample have low or intermediate level of income which is not high enough to finance all their expenses, forcing them to turn to loan market. However, as the number of the income earners in the family increases, household's need for borrowing in order to meet expenditures decreases. Somewhat surprisingly, having higher educational qualifications also lowers probability of having bank loan. This can be due to much better financial situation of highly educated individuals compared to low or even middle educated ones, especially in the later and income peaking stages of their professional career. Probability of having a bank loan decreases with age for all age brackets.

Having prior bank loans also increases the probability of repeated borrowing. Men are more likely to have debt than woman and families who have a housing loan, together with renters in 2008, tend to have higher probability of having debt than homeowners with no mortgage.

Regarding labor market status, in 2005 individuals employed in private company had higher probability of participating in credit market than all other working individuals regardless of their employment status. Retired were also less likely to have debt, but oddly others unemployed individuals had higher probability of being indebted. Higher probability of debt incident among households' whose head is unemployed can be the consequence of their effort to overcome a shorter decline in current income due to job loss in order not to have to downsize their expenditures. This is especially the case among the newly unemployed individuals who are expecting to reemploy soon. However, in 2008 only households whose head was working in public company, where less volatile wages reduce the future income uncertainty, had higher probability of having debt than those working in private sector. The effect of other employment characteristics on the probability of credit market participation is somewhat inconclusive.

As expected, households living in rural areas have lower probability of having debt than those living in more urbanized municipalities, due to limited bank supply, lower educational qualification and more widespread presence of informal credit market (Magri, 2002). Even thought it was expected that debt incident would be higher among households who have life insurance, results suggest that this was the case only in 2005.

In the second step of analysis the amount of bank loan was estimated on the sub-sample of only indebted households using quantile regressions in order to capture the changes of the effect of a various explanatory variables at different points of conditional debt distribution. In Table 4 and Table 5 we give the results for log credit estimation without and with sample selection bias correction for both observed years at nine conditional quantiles. The independent variables used are the subset of the explanatory variables used in the selection equation.

Results presented in Table 4 suggest that among the identifying variables statistically significant on almost the entire debt distribution and with expected sign are variables on the demand side: current disposable income, age of the household's head, the type of activity the head is working in, part-time work dummy and tenure status which is also connected with variables that reflect households debt supply: total number of household's bank loans and dummy identifying household with housing loan taken during the last 12 months.

Household's disposable income has positive effect on the amount of debt held in both observed years at all conditional quantiles. It is the main variable explaining the difference in holdings of bank loans. Comparing the results for 2005 and 2008 we can observe a rise in the amount of debt supported by a given size of income, accounting for most of the household debt accumulation, and especially pronounced at the tails of the debt distribution.

In 2005 households whose head is employed in company dealing in primary or secondary activity on average had lower amount of debt than households whose head works in tertiary activity, especially at lower or the highest level of indebtedness. However, in 2008 these variables showed no significance in explaining the amount of debt. Dummy variable indicating shorter working hours than usual also proved to be significant with negative sign in explaining amount of debt owed, particularly in 2008.

The impact of the age of households' head on the amount of debt depends on the individual's position in the life-cycle. The effect of the head's age on the debt is consistent with the theoretical life-cycle model of consumption; it is positive until person reaches his fifties, afterwards it becomes negative.

As expected there is a strong positive relationship between the amount of debt held and the number of loans, especially if on of them is residential loan whether new (i.e. taken during the 12 months period prior to the survey) or old one (homeowner with housing loan). This effect is observed in both years suggesting that households who already have some type of loan will have greater propensity for new borrowing. Also banks can be more willing to borrow to households who are already their clients since all relevant information about households' characteristics and regularity of servicing prior credits are already available. However, the impact of having a residential loan on the indebtedness decreased in 2008 compared to 2005.

However, when corrected for sample selectivity bias the significance of explanatory variables, together with the size of their estimated coefficients, changes significantly as can be seen from Table 5. Household's disposable income and dummy variable identifying homeowners that repay housing loan remain the most important variables in explaining the amount of debt hold in both years with unchanged sign of their effect on debt size across all conditional quantiles. In 2005 sample selection bias on the estimated coefficients of these two explanatory variables was generally downward and in 2008 mostly upward. The bias is the most pronounced for debt distribution tails. After the correction, dummy variable indicating households with new housing loan was also important in determining the size of debt along the entire debt distribution, especially in 2005. Different age brackets have statistically more significant explanatory power at different conditional quantile in 2008, together with part-time work which negatively influences the amount of debt at the higher quantiles.

4.2. Machado-Mata decomposition of household debt growth

Final step in household indebtedness analysis includes assessing the implications of changes in impacts of various explanatory variables which proxy for the evolution of "implicit" scoring models and credit policies of banks during observed pre-crises period. In order to decompose the rise of households indebtedness between 2005 and 2008 into part attributable to changes in households' creditworthiness (observed households' characteristics) and changes in banks' credit standards we follow earlier described Machado-Mata decomposition[17]. The results of MM decomposition employed on sample uncorrected for sample selectivity bias are presented in Figure 3.

Growth of indebtedness can be observed throughout the whole distribution of household debt with average rise of 27%. Rise of debt was the strongest among the highly indebted households, reaching 39% at the 99-th percentile. At the same time, characteristics of indebted households improved, which was positively reflected on the households' indebtedness dynamics. However, effect of improved households' creditworthiness can explain only around 7 percentage points of the rise of accumulated household debt across the whole indebtedness distribution. Since the effect of estimated coefficients is quantitatively more important then effect of improved households characteristics at each estimated quantile, relaxation of banks' lending standards and/or greater appetite of some households to take more credit were the main drivers of households debt growth between 2005 and 2008. On average their contribution to overall debt rise was about 18 percentage pints across whole distribution. The impact of banks' loosened implicit credit policies and growth of households' tendency to borrow was the strongest among the highly indebted households, as it explains around tree quarters of their debt increase during the observed period. At the same time the improvement of their creditworthiness was the slowest.

Overall effect of improved households' creditworthiness is decomposed into individual contributions of several characteristics that showed to be important in determining the size of debt and which represent both the demand and supply side of household credit market. Figure 4 suggests that growth of household current disposable income had positive effect upon household debt across almost the whole distribution, accounting for around 11 percentage pints increase of indebtedness. However, at the highest conditional quantiles the rise of disposable income between 2005 and 2008 was much slower. Number of bank loans that household carries is another important variable. Its impact on the debt rise is negative in the first half of distribution. However, after median it rises exponentially, positively influencing the debt dynamics. . Rising number of bank loans had positive effect on the amounts of household debt, but higher number of loans cannot be considered as an improvement of households' creditworthiness. So if the impact of the number of loans household carries is taken into account, households' creditworthiness observed at the highest conditional quantiles would actually deteriorate during observed period (see Figure 3). Age, new housing loan dummy and education, which are expected to improve creditworthiness of indebted households, didn't have a noticeable contribution to the households' debt dynamics during observed period, except among the highly indebted households where their mildly positive contribution to increasing indebtedness can be observed.

Presence of the sample selection bias can have an impact on the estimated changes to households' creditworthiness and banks' credit policies. Decomposition of households' debt

[17] MM decomposition was repeated 100 times.

rise which accounts for sample selection bias correction is presented in Figure 5. Decomposition suggests that relative improvement of households' creditworthiness would be much stronger if selection of households to which loans were granted was random. Namely, if characteristics' of indebted households had been the same as the characteristics of all households, the improvement of their creditworthiness would have been the strongest in the segment of highly indebted households, accounting for almost tree times higher percentage rise of households' debt compared to their contribution with no correction for sample selectivity bias. This implies that banks entered into more risky segments of population in with new loans, significantly shrinking differences in characteristics between their customers and households without any loans.

Overall, although there was some improvement of households' creditworthiness from 2005 to 2008, the biggest impact on the rise of the amount of household debt came from the banks' loosened credit standards, which was especially pronounced among the highly indebted households. This loosening of lending standards was even stronger if one controls for sample selection bias, indicating a relative deterioration in the creditworthiness of indebted households relative to general population.

6. Conclusions

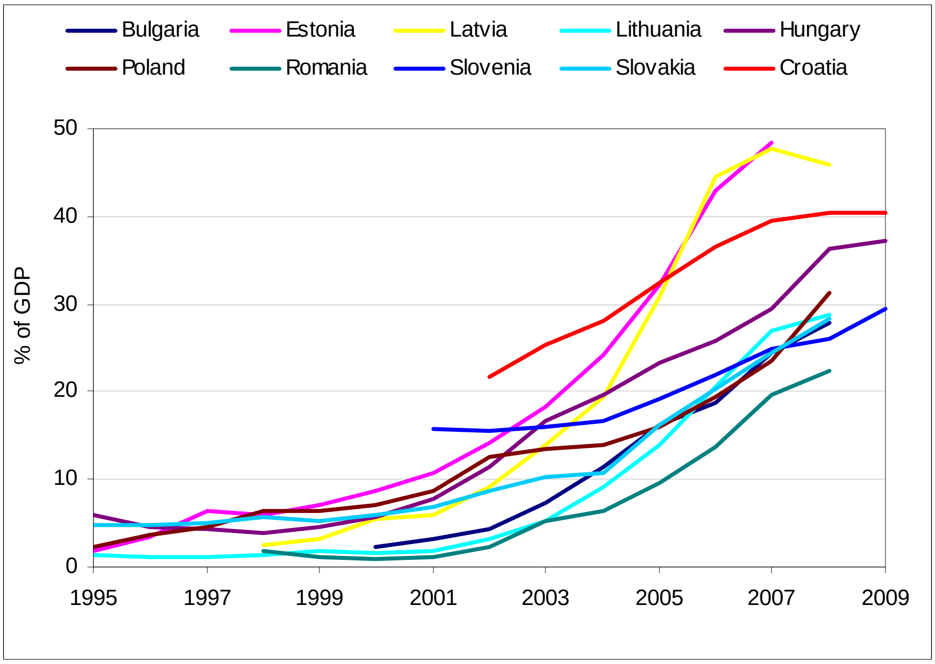
Contribution of this paper is twofold. On the one hand, it shows how a debt determination literature can be extended using techniques previously employed in the analysis of wage gaps in order to capture risks related to the dynamics of household lending. It is argued that this way has some advantages in capturing household vulnerability to shocks over previously employed methods. Such an approach uses quintile regression technique in order to observe the whole debt distribution, while being an ex ante rather than ex post way to account for household vulnerabilities, unlike most of the vulnerability indicators.

On the other hand, this paper aims to apply proposed approach in order to analyze change in the vulnerability of Croatian households arising from their higher indebtedness. It is shown that most of the debt build-up during the recent lending splurge was the result of more lenient lending and more optimistic households willing to take more debt. Although there was some improvement of households' creditworthiness over the observed period, major impact on debt growth came from relaxation of lending standards, especially for the highly indebted households, whose creditworthiness even deteriorated. Also, control for the sample selection bias shows that banks have entered into more risky segments of population with new loans, as creditworthiness of indebted households deteriorated relative to general population. While such debt dynamics increased household vulnerability at the eve of the current crises, following an even steeper debt growth, more in line with dynamics in other Central and Eastern European countries, would certainly further aggravate creditworthiness of indebted households.

Presented analysis in the current form is work in progress as there are several possible extensions. First, analysis still needs to be extended to newly indebted households, where move towards less creditworthy clients should be even more obvious. Second, a decomposition of individual contribution by individual household characteristics can be further improved, especially in equations where correction of the sample selection bias has been applied. Also, other transformations of a single index models should be considered together with some additional techniques to determine the polynomial order in series expansion. Further on, intercept in the output equation of a sample selection models should be separately identified. Finally, while changes in the debt distribution have been accounted for, some work is still needed in order to come up with the most appropriate debt concentration indicators that would capture the changing profile of the risks arising from household lending.

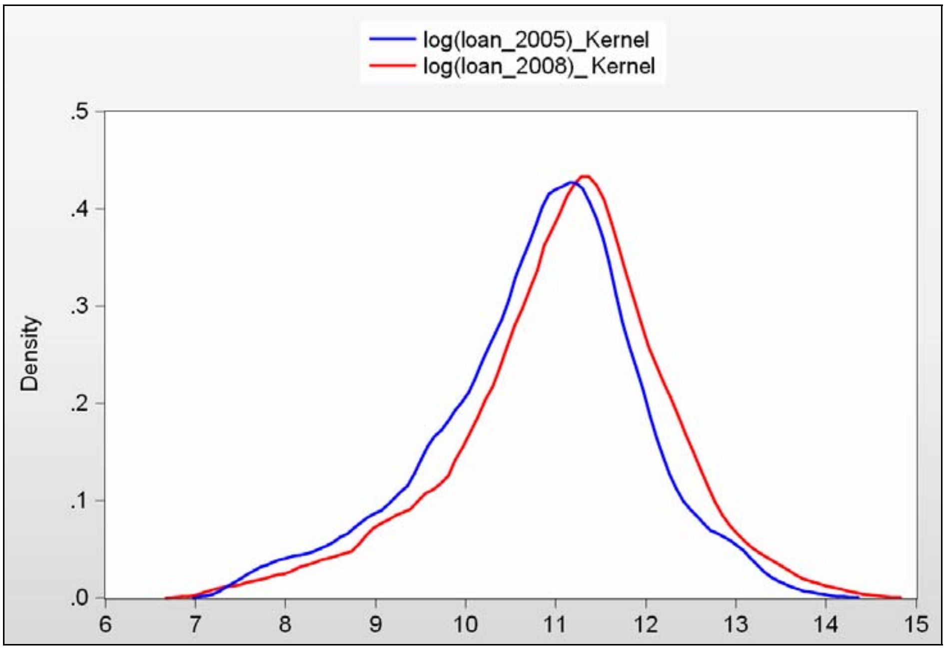
Appendix

Figure 1 Household debt



Sources: Eurostat and Croatian National Bank

Figure 2 Kernel density estimates of household debt



Source: authors' calculations based on the Household Budget Survey

Table 1 Overview of different vulnerability indicators for Croatia

Percentage of the indebted households that are vulnerable according to the:	2005	2006	2007	2008
Negative financial margin	17.51	18.31	18.66	15.85
Debt in excess of 500% of income	1.18	1.69	1.52	2.49
Repayments in excess of 30% of income	11.95	14.24	14.21	13.06
Arrears_30 days	5.68	6.89	5.31	5.28
Arrears_90 days	4.26	5.54	4.56	3.89
Perceived financial situation as very difficult	8.28	9.04	6.4	6.18
Perceived financial situation as difficult or very difficult	26.63	29.94	25.6	26.32
NPLR	4.52	4.11	3.73	3.97

More stringent combination of criteria	2005	2006	2007	2008
Arrears 30 days_only criterion	3.55	4.75	3.58	3.79
Negative financial margin_only criterion	10.53	10.96	11.50	8.97
Perceived financial situation as difficult or very difficult_only criterion	19.53	22.03	18.22	18.84
Arrears 30 days and negative financial margin	0.47	0.56	0.43	0.30
Negative financial margin and perceived financial situation as difficult or very difficult	5.44	6.33	6.07	6.28
Arrears 30 days and perceived financial situation as difficult or very difficult	0.59	1.13	0.65	0.90
Vulnerable by all three criterion	1.07	0.45	0.65	0.30
Not vulnerable	58.82	53.79	58.89	60.62
Total indebted households	100.00	100.00	100.00	100.00

Less stringent combination of criteria	2005	2006	2007	2008
Arrears 90 days_only criterion	3.31	4.41	3.36	3.39
Negative financial margin_only criterion	14.32	15.93	15.94	13.76
Perceived financial situation as very difficult_only criterion	5.80	7.01	4.23	4.19
Arrears 90 days and negative financial margin	0.71	0.68	0.76	0.30
Negative financial margin and perceived financial situation as very difficult	2.25	1.58	1.74	1.79
Arrears 90 days and perceived financial situation as very difficult	0.00	0.34	0.22	0.20
Vulnerable by all three criterion	0.24	0.11	0.22	0.00
Not vulnerable	73.37	69.94	73.54	76.37
Total indebted households	100.00	100.00	100.00	100.00

Source: authors' calculations based on the Household Budget Survey

Table 2 Descriptive statistics

		Sample of households					
		total		without debt		indebted	
Indicator	Variable	2005	2008	2005	2008	2005	2008
Mean (Std. Dev.)	DI/ in HRK	67,449.59	77,973.37	55,394.95	64,646.67	93,213.71	104,640.06
		54,694.23	59,046.96	44,739.06	55,613.53	64,315.27	56,662.26
	DI_pc/ in HRK	25,695.09	30,163.81	23,926.31	28,292.25	29,475.46	33,908.78
		19,038.51	19,921.37	16,278.38	19,871.82	23,459.82	19,497.41
	Loan/ in HRK	27,085.77	38,254.92	0.00	0.00	84,975.60	114,802.90
		70,835.53	103,942.64	0.00	0.00	104,064.83	153,778.62
	New_loan/ in HRK	6,014.44	7,908.99	0.00	0.00	18,868.96	23,734.86
		29,070.00	43,613.88	0.00	0.00	49,096.88	73,049.35
	No. household members	2.82	2.76	2.50	2.43	3.51	3.41
		1.57	1.59	1.52	1.53	1.46	1.51
	No. employed members	1.07	1.09	0.84	0.85	1.56	1.58
		1.04	1.07	0.99	1.00	0.98	1.05
	No. children	0.57	0.50	0.43	0.38	0.85	0.74
		1.00	0.93	0.94	0.88	1.06	0.98
	No. loans	0.43	0.45	0.00	0.00	1.34	1.35
		0.75	0.74	0.00	0.00	0.66	0.67
	Age/ years	57.31	58.82	60.24	61.59	51.07	53.28
		15.12	14.72	15.32	14.94	12.57	12.57
%	<30	2.60	2.66	2.49	2.74	2.84	2.49
	30-39	11.28	7.74	8.31	6.33	17.63	10.57
	40-49	18.86	17.81	15.12	12.81	26.86	27.82
	50-59	22.48	23.29	19.44	20.08	28.99	29.71
	60-69	19.43	21.56	21.82	23.27	14.32	18.15
	>70	25.35	26.94	32.83	34.78	9.35	11.27
	Male	69.52	67.28	66.22	63.83	76.57	74.18
	Female	30.48	32.72	33.78	36.17	23.43	25.82
	Homeowner without housing loan	79.33	75.08	87.87	84.06	61.07	57.13
	Homeowner with housing loan	8.34	13.49	0.00	4.19	26.15	32.10
	Renter	12.33	11.43	12.13	11.76	12.78	10.77
	New housing loan	1.06	1.46	0.00	0.00	3.31	4.39
	Single	7.66	6.84	9.25	8.22	4.26	4.09
	Widow	23.39	24.82	28.29	30.54	12.90	13.36
	Married	64.16	62.56	57.53	55.46	78.34	76.77
	Separated	4.79	5.78	4.93	5.78	4.50	5.78
	Education_low	38.36	36.48	46.01	44.29	22.01	20.84
	Education_middle	48.81	50.13	43.85	44.74	59.41	60.92
	Education_high	12.83	13.39	10.13	10.96	18.58	18.25
	Works	47.42	46.25	39.20	37.87	64.97	63.01
	Doesn't Work	52.58	53.75	60.80	62.13	35.03	36.99
	Entrepreneur	4.15	4.78	3.27	4.88	6.04	4.59
	Farmer	8.83	8.54	10.41	9.32	5.44	6.98
	Public company	14.30	13.59	8.31	8.22	27.10	24.33
	Private company	17.31	17.44	14.40	13.30	23.55	25.72
	Retired	43.61	46.45	50.06	53.46	29.82	32.40
	Other_works	2.83	1.89	2.82	2.14	2.84	1.40
	Other_doesn't work	8.98	7.31	10.74	8.67	5.21	4.59
	Activity_primary	22.12	22.84	30.93	29.74	10.75	14.56
	Activity_secundary	30.79	30.39	29.24	28.16	32.79	33.07
	Activity_tertiary	47.10	46.77	39.83	42.11	56.47	52.37
	Contract_permanent	88.57	90.09	85.82	85.71	92.12	95.37
	Contract_determinante	4.96	3.69	5.39	4.89	4.40	2.23
	Contract_others	6.47	6.22	8.79	9.39	3.48	2.39
	Working time_full	73.94	76.64	68.79	68.87	80.59	86.12
	Working part-time	12.47	13.23	16.60	19.07	7.14	6.22
	Working longer than full-time	13.59	10.05	14.61	12.05	12.27	7.66
	Rural area of residence	47.49	49.70	51.72	53.81	38.46	41.48
	Life_insurance	7.54	8.50	4.21	4.63	14.67	16.25

Source: authors' calculations based on the Household Budget Survey

Table 3 Semiparametric least squares estimates for the selection equation

Explanatory variables	Reference household	2005	2008
log(disposable income)		1	1
number of children		-0.047	-0.193
number of loans		5.913	5.407
number of employed members		-0.292	-0.275
marital status			
separated	married	-0.182	0.596
single		0.489	0.510
widow		0.866	-0.180
age			
<30	50-59	-1.139	-0.814
30-39		-0.154	-0.298
40-49		-0.007	-0.588
60-69		-0.180	-0.084
>70		-0.839	-0.716
female	male	-0.858	-0.044
level of education			
low	middle	0.332	1.137
high		-0.612	-0.617
housing tenure			
homeowner with housing loan	homeowne without home loan	0.115	0.475
renter		-0.077	0.192
new housing loan	no new home loan	0.290	1.681
employment status			
public company	private company	-0.639	0.144
entrepreneur		-0.439	-0.751
retired		-0.246	-1.330
farmer		-0.443	-1.025
other_works		-0.921	-0.362
other_doesn't work		0.207	-0.139
type of activity			
primary	tertiary	-0.742	0.438
secundary		0.181	-0.698
working time			
part-time	full-time	0.772	-0.383
longer then full-time		-0.469	0.525
working contract			
determinante	permanent	0.409	-0.815
other		-0.757	-1.583
rural area of residence	urban area of residence	-0.630	-0.795
life insurance	no life insurance	0.420	-0.580

Notes:
The SLS estimator is Ichimura's (1993) estimator.
All the coefficients are calculated relative to the absolute value of the coefficient on the disposable income.
Source: authors' calculations based on the Household Budget Survey

Table 4 Results of the estimation of the size of a loan using quantile regression (without sample selection bias correction)

Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
c	4.4896	-0.2534	3.7040	0.3250	3.9784	1.7982	4.4380	1.8801	5.0061	2.5842	5.4353	3.6695	6.8298	3.7844	7.0777	3.6302	6.5070	3.0883
	3.3782***	-0.0746	2.7147***	0.2078	2.8330***	1.9581*	3.8979***	1.8333*	3.9040***	2.8008***	4.2002***	4.0096***	7.6871***	4.5417***	10.3102***	3.1668***	8.6595***	2.1100**
log(disposable income)	0.3996	0.7723	0.5032	0.8011	0.5185	0.7081	0.4908	0.7324	0.4493	0.6845	0.4338	0.6047	0.3336	0.5998	0.3314	0.6529	0.4168	0.7227
	3.2097***	2.5308***	3.9530***	5.6509***	4.0851***	8.2923***	4.6200***	7.8477***	3.7090***	8.0928***	3.6087***	7.1535***	4.0535***	7.8592***	5.0200***	6.1392***	5.4889***	5.3829***
No. children	0.1742	0.0448	0.0573	0.0061	0.0406	0.0450	0.0172	0.0218	0.0252	0.0261	0.0104	0.0694	0.0121	0.0628	0.0116	0.0987	0.0650	0.0400
	2.7453***	0.5009	1.0741	0.1262	0.8017	1.0365	0.3807	0.4766	0.5792	0.5455	0.2485	1.6210	0.3289	1.5526	0.2854	2.2459**	1.2433	0.7445
No. loans	0.5768	0.5291	0.5268	0.5312	0.4324	0.5048	0.4275	0.4667	0.4724	0.4755	0.4600	0.4381	0.4179	0.4464	0.3722	0.3576	0.3528	0.4065
	7.9758***	3.3150***	8.0155***	9.3491***	6.1176***	10.5435***	7.4364***	10.2763***	8.8646***	9.9444***	9.3164***	9.3144***	8.7373***	9.1593***	7.1724***	6.7302***	5.2542***	4.0787***
No. employed members	-0.0272	0.0061	-0.0056	0.0012	-0.0334	-0.0187	-0.0155	-0.0532	-0.0048	-0.0093	-0.0323	-0.0078	-0.0111	0.0208	-0.0166	-0.0455	-0.1023	-0.0861
	-0.2748	0.0424	-0.0642	0.0169	-0.5033	-0.3420	-0.2592	-0.9835	-0.0784	-0.1743	-0.5500	-0.1435	-0.2055	0.4364	-0.2782	-0.8423	-1.5116	-1.4425
separated	0.4265	0.4716	0.2878	0.2167	0.2601	0.0440	0.1945	-0.0038	0.0901	0.2213	0.0200	0.0892	-0.0262	0.0442	-0.0495	-0.0974	-0.1676	-0.0396
	1.3644	1.0727	1.1888	1.2757	1.2201	0.2758	1.0340	-0.0194	0.4439	1.5430	0.0989	0.7178	-0.1373	0.3916	-0.2783	-0.8287	-1.0030	-0.2233
single	0.2863	0.3378	0.0307	0.3365	0.0368	0.0931	-0.0423	-0.0205	-0.0877	-0.0699	-0.2378	0.0378	-0.1408	0.0020	-0.1970	-0.0191	-0.1032	0.1334
	0.7091	0.2577	0.0587	1.8112*	0.1941	0.6567	-0.2439	-0.1310	-0.4324	-0.4092	-1.1267	0.1763	-0.6036	0.0106	-0.8767	-0.0999	-0.3670	0.6039
widow	0.2511	0.3289	0.1263	0.0628	0.0613	0.0430	0.1300	-0.0217	0.0399	0.1571	0.1232	0.1324	0.1432	0.1832	0.0470	0.1919	-0.1370	0.2964
	0.8111	0.7345	0.5950	0.2867	0.3189	0.2683	0.6936	-0.1261	0.2157	0.8167	0.6599	0.8178	0.7881	1.3126	0.2681	1.3237	-0.7714	1.6405
<30	-0.5546	0.2231	0.2599	0.1424	0.4971	0.0636	0.3921	0.3008	0.2112	0.4471	0.3827	0.3205	0.2868	0.5245	0.4633	0.4209	0.5515	0.4571
	-1.6563*	0.1526	0.3452	0.3799	1.7253*	0.2368	1.6084	1.0532	0.8615	1.8774*	1.5835	1.0954	1.2560	2.1876**	1.9131*	1.7269*	1.2373	1.7965*
30-39	-0.1312	0.4043	0.1292	0.4659	0.1789	0.3039	0.1688	0.3511	0.1900	0.3754	0.2540	0.2923	0.3259	0.2766	0.3103	0.2439	0.2890	0.3389
	-0.6525	1.0944	0.6052	3.1517***	1.1656	2.4161**	1.2493	2.6814***	1.3882	3.0016***	1.8978*	2.4163**	2.4558**	2.4101**	2.3976**	2.0932**	1.7253*	2.2876**
40-49	-0.1112	0.3505	0.1240	0.2926	0.1419	0.2722	0.0903	0.2567	0.1171	0.2894	0.1968	0.2337	0.2608	0.2555	0.2239	0.1709	0.2923	0.2213
	-0.5855	1.7019*	0.8037	1.8445*	1.0796	2.9851***	0.7572	2.8993***	0.9946	3.3500***	1.831*	2.5565**	2.7412***	2.8029***	2.4288**	1.735*	2.5795**	1.8373*
60-69	-0.2130	-0.2079	-0.3115	-0.1756	-0.1863	-0.2276	-0.1964	-0.1732	-0.1472	-0.1005	-0.0546	-0.0613	-0.0584	-0.0903	-0.0316	-0.0824	0.0968	-0.1121
	-1.1159	-0.6636	-1.4498	-1.1088	-0.8991	-1.8671*	-1.1265	-1.2962	-0.9564	-0.8171	-0.3848	-0.5539	-0.4340	-0.8809	-0.2051	-0.7972	0.7109	-0.7960
>70	-0.6063	-0.3563	0.0916	-0.5276	0.1223	-0.4593	-0.0300	-0.3802	-0.0098	-0.3541	0.0276	-0.2770	-0.0377	-0.2605	-0.0372	-0.2910	0.1081	-0.3110
	-2.2572**	-0.9123	0.3601	-2.5735**	0.5789	-2.7187***	-0.1804	-2.5439**	-0.0603	-2.3552**	0.1761	-1.8749*	-0.2357	-1.9035*	-0.2274	-1.8177*	0.5577	-1.6684*

Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
female	-0.2501	-0.1246	-0.1546	-0.0383	-0.2403	-0.0335	-0.2374	0.0328	-0.1105	0.0690	-0.0531	0.0641	-0.0987	0.1120	-0.0324	0.0921	0.0806	-0.0401
	-0.8101	-0.2571	-0.8254	-0.2434	-1.7781*	-0.2775	-1.6882*	0.2506	-0.8015	0.5663	-0.3818	0.6714	-0.7572	1.3330	-0.2332	1.0878	0.5728	-0.3217
low education	-0.1222	0.0036	-0.0862	-0.0522	-0.1792	-0.1612	-0.1936	-0.1534	-0.1997	-0.1924	-0.1009	-0.0869	-0.0718	-0.0146	-0.1781	-0.0501	-0.1953	0.0210
	-0.6399	0.0172	-0.5115	-0.3697	-1.3095	-1.6905*	-1.5098	-1.5630	-1.5783	-1.821*	-0.8943	-0.7828	-0.7309	-0.1467	-1.9028*	-0.5226	-1.7406*	0.1555
high education	0.0586	0.0842	-0.0300	0.1736	0.0565	0.1662	0.0532	0.1324	0.0332	0.0554	0.0234	0.0694	0.0883	0.1215	0.0544	0.0962	0.1465	0.2940
	0.3274	0.2552	-0.1884	1.2564	0.4100	1.7876*	0.4732	1.4625	0.3089	0.6642	0.2274	0.8277	0.8484	1.4601	0.4819	0.9191	0.8899	1.7581*
homeowner with housing loan	0.7484	0.8220	0.6212	0.5132	0.5838	0.4941	0.6202	0.4027	0.5829	0.3307	0.5481	0.3365	0.5478	0.3617	0.5433	0.3725	0.4997	0.5036
	5.4135***	4.1500***	5.0046***	4.3126***	5.2151***	6.2136***	6.4856***	4.9888***	6.5298***	4.4324***	6.1605***	4.5192***	5.9074***	4.7696***	5.2904***	3.9990***	4.2908***	3.7478***
renter	-0.1791	0.3040	-0.1644	0.0664	-0.1813	0.0782	-0.0861	-0.0945	-0.0822	-0.1296	-0.1098	-0.1046	-0.1589	-0.1752	-0.0618	-0.1188	-0.0948	-0.1802
	-0.7745	0.8280	-0.7625	0.5144	-1.1042	0.7533	-0.6166	-0.8484	-0.6110	-1.3284	-0.8387	-1.0478	-1.2816	-1.8508*	-0.4417	-1.2005	-0.6803	-1.5291
new housing loan	0.9722	0.1459	0.6576	0.0240	0.4313	0.0492	0.4325	0.3666	0.5312	0.2332	0.4042	0.3743	0.4824	0.3835	0.6379	0.4088	0.5537	0.1889
	6.2932***	0.6234	3.7057***	0.0905	2.3670**	0.1978	1.6231	2.0320**	2.6228***	1.3757	2.0277**	1.8934*	1.3808	2.0578**	2.7048***	2.7610***	2.5614**	1.2415
public company	0.0896	0.0995	0.0826	-0.2055	0.1372	-0.1979	0.1546	-0.2030	0.1631	-0.1135	0.1163	-0.0337	0.0721	-0.0066	0.0998	0.0135	0.0826	0.0201
	0.4064	0.4154	0.4997	-1.4616	1.0582	-1.9828**	1.3493	-1.9743**	1.4699	-1.1825	1.1014	-0.3680	0.7158	-0.0782	0.9545	0.1409	0.5347	0.1714
entrepreneur	-0.0676	0.2662	0.0575	0.1984	0.0714	0.2102	0.2154	0.1202	0.1589	0.1301	0.0411	0.1366	-0.0405	0.2060	0.1273	0.4246	-0.1025	0.5557
	-0.1761	0.5720	0.1706	0.7067	0.3130	1.3923	1.0951	0.8761	0.8313	0.9260	0.2357	0.9388	-0.2375	1.2245	0.6286	1.5317	-0.4181	2.2494**
retired	-0.4826	0.0053	-0.3142	-0.0100	-0.2466	-0.0207	-0.0866	-0.0909	-0.0479	-0.0470	-0.1527	-0.0900	-0.1751	-0.0773	-0.0612	-0.0750	-0.1327	-0.0407
	-1.4495	0.0148	-1.4291	-0.0460	-1.2714	-0.1468	-0.4846	-0.6321	-0.2850	-0.3725	-0.9612	-0.6934	-1.1918	-0.6351	-0.3955	-0.5420	-0.8499	-0.1945
farmer	1.1574	1.2566	1.1957	0.8726	0.2974	0.4144	0.1843	0.4846	0.3572	0.2997	0.5427	0.3113	0.1736	0.2260	0.2934	0.5818	0.4649	0.5341
	1.897*	1.8202*	2.2551**	1.2349	0.3339	0.8820	0.5552	1.5159	1.0381	1.1503	1.4612	0.9266	0.5628	0.7697	0.9105	1.9566*	1.4459	1.6169
other_works	0.0001	0.6037	0.3220	0.0875	0.5508	0.0143	0.2609	-0.1735	0.3707	-0.2615	0.3271	-0.1684	0.3027	0.0842	0.2995	0.9267	-0.0236	0.5835
	0.0004	1.3603	0.5250	0.4121	1.0932	0.0925	0.6923	-0.9917	1.7376*	-1.5257	1.5926	-0.6585	1.5723	0.1192	1.5391	2.9793***	-0.1262	1.5131
other_doesn't work	0.0017	0.1954	0.1278	0.1891	0.1003	0.0917	0.0260	-0.0133	0.1685	-0.0070	0.1267	0.1399	-0.0185	0.1283	0.1121	0.0404	0.1029	0.1259
	0.0034	0.4326	0.5317	0.5638	0.5153	0.5164	0.1318	-0.0637	0.8543	-0.0346	0.6296	0.7536	-0.0996	0.7342	0.6288	0.2586	0.4951	0.6357
primary activity	-1.1674	-0.9230	-1.3670	-0.6684	-0.5443	-0.1640	-0.2770	-0.1301	-0.4620	-0.0766	-0.5878	-0.0956	-0.4551	-0.0497	-0.5474	-0.0053	-0.6893	0.0805
	-2.8694***	-1.3301	-3.1575***	-0.9726	-0.6463	-0.3822	-1.1116	-0.4401	-1.6956*	-0.3380	-2.3079**	-0.3174	-2.3145**	-0.1953	-2.4036**	-0.0217	-2.7506***	0.2925
secundary activity	-0.6228	0.1197	-0.4234	-0.0315	-0.2470	-0.0368	-0.1355	-0.0092	-0.1098	-0.0818	-0.1697	-0.0968	-0.2692	-0.0976	-0.1239	-0.0539	-0.0199	-0.0759
	-2.1920**	0.4758	-1.9756**	-0.2123	-1.8116*	-0.4303	-1.1796	-0.1079	-0.9672	-0.9926	-1.6182	-1.1425	-2.8248***	-1.1166	-1.1456	-0.5787	-0.1572	-0.6338

Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
part-time	-0.5909	-0.5170	-0.4987	-0.2765	-0.1476	-0.4218	-0.2437	-0.4806	-0.1283	-0.5401	-0.0478	-0.5843	0.1724	-0.4907	0.2386	-0.7357	0.2395	-0.8928
	-2.2917**	-1.0574	-1.4271	-1.0465	-0.5980	-2.1224**	-1.0271	-2.6854***	-0.4773	-3.2336***	-0.1545	-3.1220***	0.4858	-2.4733**	0.6872	-4.0741***	0.7062	-4.7675***
longer than full-time	-0.1200	0.0088	-0.2153	0.1966	-0.1500	0.2261	-0.1505	0.1129	-0.0108	-0.0525	0.0789	-0.0343	0.1271	-0.1268	0.0958	-0.2218	0.1882	-0.1253
	-0.4766	0.0187	-0.7750	0.6630	-0.6265	1.86*	-0.6590	0.9136	-0.0505	-0.4107	0.4670	-0.2770	0.8787	-0.9977	0.6176	-1.1181	0.8799	-0.7795
determinante contract	0.4704	0.4529	0.2807	0.0927	0.1358	0.0549	0.4655	0.0421	0.3106	-0.2339	0.1749	-0.1948	0.0599	-0.2045	-0.1000	0.0826	0.0637	-0.1429
	1.4975	0.6973	0.9610	0.3543	0.3750	0.4033	2.4291**	0.3428	1.6316	-1.761*	0.9611	-1.3039	0.3521	-1.1866	-0.6235	0.2699	0.1912	-0.4495
other contract	0.1462	0.0223	0.0948	0.5549	-0.1976	0.4070	0.1329	0.4964	-0.0462	0.6087	-0.3564	0.5132	-0.5266	0.3210	-0.4166	-0.0010	-0.2384	0.1606
	0.3403	0.0186	0.2210	1.5585	-0.4884	1.7131*	0.3854	2.1856**	-0.1585	3.0339***	-1.3238	2.2258**	-1.8247*	1.1570	-0.8833	-0.0043	-0.6543	0.4035
Observations:	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003
Adjusted R-squared:	0.2251	0.2357	0.1952	0.2201	0.1901	0.2156	0.1795	0.2068	0.1769	0.1968	0.1703	0.2038	0.1752	0.2095	0.1902	0.2204	0.2210	0.2307

Notes:
t- statistics is given in the second line.
***, significant at 1% level
**, significant at 5% level
*, significant at 10% level
Source: authors' calculations based on the Household Budget Survey

Table 5 results of the estimation of the size of a loan using quantile regression corrected for sample selection bias

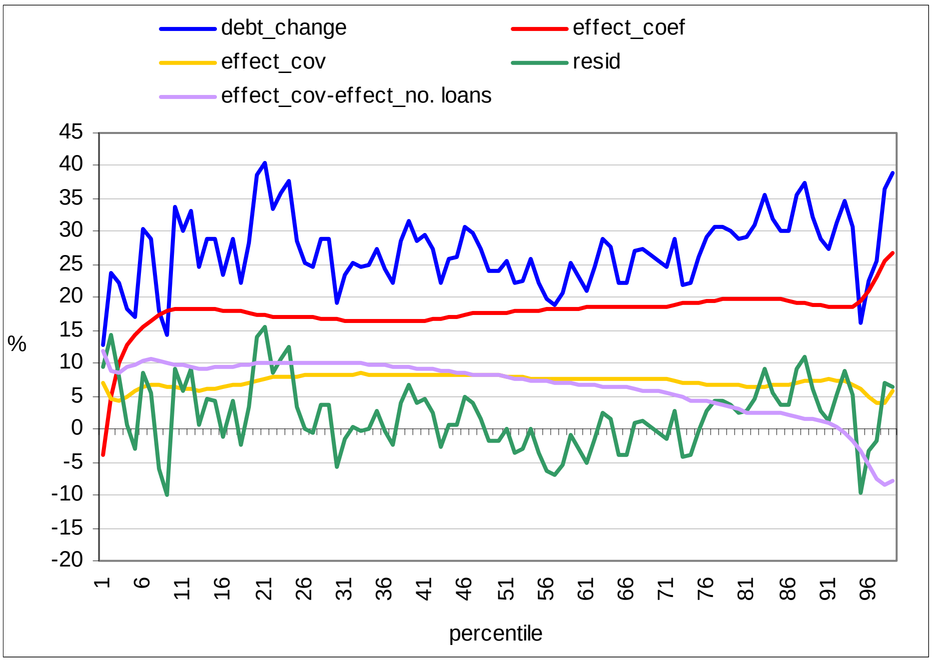
Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
c	76.5026	5.9283	68.7499	42.7927	62.4101	29.4827	56.0958	11.0551	-6.3069	1.0987	-27.0927	3.4708	-46.6190	3.6533	-42.9202	-6.8929	-58.6895	-7.9897
	1.0104	0.0851	1.4791	1.9395*	1.4373	1.6015	1.6787*	0.3566	-0.1917	0.0645	-0.7980	0.2024	-1.4986	0.1763	-1.3365	-0.3278	-1.6717*	-0.3257
log(disposable income)	0.8042	0.4461	0.8479	0.6583	0.7033	0.7461	0.6736	0.7164	0.5315	0.6279	0.4867	0.6348	0.5415	0.6474	0.5068	0.6590	0.6513	0.5904
	2.5614**	1.2930	3.6409***	3.6077***	3.4175***	6.2382***	3.6861***	5.7201***	2.6555***	5.6155***	2.7402***	5.4230***	3.3621***	5.5779***	3.2086***	4.3769***	3.5624***	3.6873***
No. children	0.1333	0.0758	0.0287	0.0157	0.0056	0.0341	0.0051	0.0521	0.0240	0.0505	0.0122	0.0631	0.0061	0.0583	-0.0028	0.0775	0.0110	0.0617
	2.1604**	0.8020	0.5234	0.2888	0.1041	0.7342	0.1124	1.0356	0.5842	1.1126	0.3190	1.4397	0.1679	1.3307	-0.0667	1.6360	0.2065	1.0229
No. loans	2.2095	-0.7722	2.6486	0.2385	1.3609	0.5053	1.5368	0.4909	1.3731	0.4341	1.2322	0.9084	1.5863	0.6991	1.3313	0.5940	1.4891	0.4556
	1.1877	-0.4572	1.9968**	0.3236	1.2192	0.9962	1.8214*	0.9248	1.7613*	0.9118	1.691*	1.957*	2.2424**	1.4107	1.8944*	1.1976	1.7961*	0.6801
No. employed members	-0.2519	0.1103	-0.1225	0.0584	-0.0590	-0.0287	-0.0410	-0.0430	-0.0529	-0.0071	-0.0396	-0.0223	-0.0785	0.0067	-0.0982	-0.0557	-0.1982	-0.0689
	-1.5647	1.0312	-1.0703	0.6810	-0.7077	-0.4568	-0.6106	-0.6673	-0.7015	-0.1196	-0.5485	-0.3463	-1.1034	0.1063	-1.3163	-0.7959	-2.5426**	-0.9938
separated	0.3883	0.3587	0.0255	0.1474	0.0903	0.1118	0.2364	0.0807	0.1132	0.1804	0.1464	0.1135	0.0036	0.0617	-0.0997	-0.0940	-0.1604	-0.0420
	1.5512	0.9534	0.1061	0.7154	0.3431	0.6198	1.1806	0.4088	0.5389	1.2266	0.7435	0.9301	0.0205	0.5202	-0.5519	-0.6569	-0.8485	-0.1900
single	0.3333	0.1646	0.1744	0.3319	0.1118	0.1042	-0.0446	0.0340	-0.0383	-0.0987	-0.0883	0.0662	-0.0587	0.0659	-0.0609	-0.0075	-0.1423	0.0240
	1.1600	0.1292	0.4878	2.1414**	0.5551	0.7072	-0.2047	0.2053	-0.1756	-0.5734	-0.3882	0.3139	-0.2589	0.3134	-0.2498	-0.0357	-0.4866	0.1229
widow	0.4223	0.3458	0.3289	0.0415	0.1784	0.0092	0.0804	-0.0090	0.1461	0.0903	0.1737	0.1538	0.2272	0.1737	0.0385	0.2099	0.0626	0.1911
	1.2201	1.0170	1.3283	0.2102	0.8716	0.0542	0.3938	-0.0483	0.6890	0.4604	0.9124	1.0109	1.2370	1.2501	0.1985	1.4344	0.2900	1.1425
<30	-1.0981	0.5931	-0.3725	0.1812	0.2506	0.0162	0.0575	0.3057	0.1844	0.3339	0.3235	0.3096	0.1657	0.5125	0.2991	0.4455	0.5816	0.3802
	-1.6732*	0.4381	-0.5070	0.4738	0.6224	0.0594	0.1720	1.1288	0.7281	1.2395	1.3478	0.9879	0.7193	1.6983*	1.1141	1.6253	1.2530	1.6596*
30-39	-0.2194	0.5715	0.0221	0.4827	0.1544	0.2930	0.0810	0.3381	0.1611	0.4038	0.2233	0.2744	0.3265	0.2742	0.2987	0.2715	0.3083	0.3061
	-0.8781	1.8598*	0.1180	3.5323***	0.9111	2.2706**	0.5808	2.4359**	1.2201	3.3265***	1.7319*	2.2586**	2.5563**	2.1842**	2.2323**	2.0051**	1.8465*	1.9252*
40-49	-0.1814	0.5853	0.1480	0.3224	0.1144	0.2216	0.0248	0.2438	0.1585	0.2686	0.1759	0.2103	0.2199	0.2225	0.2437	0.1577	0.3030	0.2702
	-0.9910	2.9831***	1.0372	2.0356**	0.9373	1.9968**	0.2248	2.3336**	1.4413	2.5153**	1.7204*	1.9052*	2.2418**	1.9526*	2.6283***	1.2506	2.9035***	1.9408*
60-69	-0.2716	-0.1837	-0.3188	-0.1731	-0.1998	-0.2543	-0.2825	-0.0907	-0.1708	-0.1543	-0.1295	-0.0860	-0.1468	-0.0687	-0.0969	-0.0911	0.0962	-0.0578
	-1.3228	-0.7329	-1.4199	-1.1033	-0.9810	-1.9030*	-1.6366	-0.6429	-1.0626	-1.2594	-0.9223	-0.7948	-1.0743	-0.6831	-0.5848	-0.8491	0.7323	-0.3847
>70	-0.8067	-0.3339	-0.2103	-0.4724	0.0032	-0.4693	-0.1224	-0.3062	-0.0456	-0.3147	-0.0381	-0.3093	-0.2283	-0.2476	-0.1561	-0.3308	0.0026	-0.3249
	-2.2373**	-1.2175	-0.6476	-2.0396**	0.0127	-2.7500***	-0.6309	-1.7046*	-0.2494	-1.9490*	-0.2253	-2.1245**	-1.3766	-1.6960*	-0.8713	-1.7947*	0.0114	-1.6001

Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
female	-0.3042	-0.2436	-0.3174	-0.0431	-0.3465	-0.0081	-0.3422	0.0428	-0.2008	0.1404	-0.0975	0.0707	-0.1312	0.1506	-0.0557	0.1090	-0.1178	-0.0471
	-0.9293	-0.7873	-1.4407	-0.2891	-2.0690**	-0.0643	-2.1536**	0.3316	-1.2976	1.1542	-0.6608	0.7583	-0.9296	1.7622*	-0.3514	1.2348	-0.6345	-0.3550
low education	-0.1074	-0.2610	-0.0652	-0.0892	-0.1099	-0.1469	-0.1039	-0.1807	-0.1612	-0.2191	-0.1166	-0.0154	-0.0721	0.0049	-0.1448	-0.0418	-0.1675	-0.0902
	-0.5260	-1.0098	-0.4039	-0.5272	-0.7469	-1.1383	-0.8865	-1.3893	-1.3277	-1.6114	-1.0854	-0.1189	-0.7456	0.0378	-1.5131	-0.3028	-1.3787	-0.5166
high education	-0.2973	0.2072	-0.1990	0.2290	-0.1289	0.1121	-0.1121	0.1471	0.0328	0.0870	-0.0333	0.0284	-0.0398	0.1140	-0.0770	0.1013	-0.0156	0.2800
	-1.1506	0.6952	-1.0915	1.4963	-0.8114	1.0289	-0.7978	1.5363	0.2559	0.9521	-0.2827	0.3143	-0.3309	1.1394	-0.5681	0.8141	-0.0812	1.8896*
homeowner with housing loan	0.7772	0.4994	0.6753	0.4821	0.5670	0.5014	0.6298	0.4274	0.6065	0.3092	0.5761	0.3895	0.5770	0.3951	0.5913	0.3708	0.5503	0.3856
	4.3078***	2.3407**	4.4909***	3.6098***	4.6535***	5.2214***	6.4924***	4.3313***	6.7985***	3.4592***	6.4074***	4.2427***	5.8568***	4.1122***	5.5706***	2.8793***	4.2558***	2.3505**
renter	-0.2936	0.2159	-0.1347	0.1120	-0.1205	0.1066	-0.0377	-0.0236	-0.0962	-0.1839	-0.1289	-0.1015	-0.1858	-0.0818	-0.0587	-0.1373	-0.0047	-0.2950
	-1.1018	1.0923	-0.6246	0.8077	-0.7940	0.9371	-0.3001	-0.1982	-0.8239	-1.7374*	-1.1120	-0.9812	-1.5230	-0.7906	-0.4059	-1.3215	-0.0285	-2.3722**
new housing loan	0.9254	-0.1845	0.7110	-0.0593	0.4356	0.0495	0.5842	0.3342	0.5464	0.1851	0.3892	0.3737	0.7248	0.3911	0.7016	0.4503	0.5883	0.2123
	5.0581***	-0.4486	3.4081***	-0.2183	2.0351**	0.1569	3.2309***	1.4781	2.5702**	0.9045	1.8298*	1.6425	2.8417***	1.5272	3.1774***	2.1609**	2.1469**	0.8336
public company	-0.2860	-0.0514	-0.2060	-0.2099	-0.0386	-0.1880	-0.0175	-0.1787	0.0451	-0.1308	0.0327	0.0010	-0.0025	0.0067	-0.0125	0.0418	-0.0334	-0.0789
	-0.9024	-0.2672	-0.8196	-1.6390	-0.2025	-1.8288*	-0.1137	-1.7272*	0.2996	-1.3433	0.2446	0.0103	-0.0191	0.0767	-0.0994	0.4306	-0.2224	-0.6993
entrepreneur	-0.5109	0.6331	-0.0782	0.2908	0.0299	0.1537	0.1512	0.1523	0.0709	0.1914	0.0128	0.1212	-0.1061	0.1927	0.1490	0.3958	0.0224	0.5090
	-0.8434	1.2934	-0.3031	1.0869	0.1245	0.8623	0.7655	0.8838	0.3810	1.1796	0.0799	0.7211	-0.6794	0.9836	0.6385	1.3589	0.0857	1.724*
retired	-0.9248	0.3377	-0.4449	0.0658	-0.3606	-0.0321	-0.1511	-0.1145	-0.1410	0.0433	-0.1781	-0.1669	-0.1415	-0.1401	-0.0762	-0.1020	-0.2000	0.0199
	-2.3818**	1.0545	-1.9499*	0.2390	-1.7105*	-0.1604	-0.8773	-0.5148	-0.8146	0.2365	-1.1141	-0.9052	-0.9052	-0.7872	-0.4669	-0.5094	-1.4155	0.0624
farmer	0.6905	1.6592	0.7505	0.9821	0.2672	0.4174	0.0495	0.3077	0.2333	0.2535	0.1850	0.2840	-0.0119	0.1703	0.0358	0.6495	0.2463	0.5419
	0.9701	2.5705**	1.2511	1.0730	0.2956	0.8126	0.1279	1.0541	0.6435	0.9319	0.5606	0.9364	-0.0408	0.5322	0.1096	1.9022*	0.7404	1.6051
other_works	-0.3318	0.5937	0.1407	0.0783	0.4141	-0.0479	0.3529	-0.2678	0.4937	-0.3873	0.3502	-0.2793	0.2137	-0.0369	0.1708	0.8924	-0.1538	0.7302
	-0.8186	2.1528**	0.2597	0.4711	0.9145	-0.3284	1.1795	-1.5270	2.0994**	-2.2590**	1.5144	-1.3332	0.9543	-0.0396	0.8176	2.3680**	-0.7378	2.3334**
other_doesn't work	-0.4487	0.0368	0.0542	0.0257	-0.0302	0.1016	0.0566	0.0809	0.0170	0.0216	0.0193	0.0636	0.0691	0.1287	0.1008	0.0129	0.1299	0.0510
	-0.8605	0.0663	0.2330	0.0798	-0.1584	0.5402	0.3260	0.3784	0.0893	0.1096	0.0932	0.3388	0.3308	0.7235	0.5438	0.0761	0.5617	0.2627
primary activity	-1.3043	-1.1030	-1.4241	-0.6570	-0.7270	-0.1520	-0.4889	0.0582	-0.4178	-0.0028	-0.4216	-0.1301	-0.3674	0.0181	-0.3194	-0.0224	-0.5000	0.0158
	-2.8302***	-2.3770**	-3.2118***	-0.6732	-0.8178	-0.3231	-1.4178	0.2413	-1.3362	-0.0128	-1.4870	-0.4744	-1.3824	0.0674	-1.0209	-0.0872	-1.5313	0.0550
secundary activity	-0.6619	0.1818	-0.4790	-0.0331	-0.2640	-0.0408	-0.1813	-0.0094	-0.1396	-0.0293	-0.1878	-0.1365	-0.1798	-0.1040	-0.1243	-0.0600	0.1108	-0.1654
	-2.4792**	0.7478	-2.4205**	-0.2076	-1.8105*	-0.3350	-1.6017	-0.0758	-1.3614	-0.2711	-1.9403*	-1.3200	-1.8668*	-0.9285	-1.0469	-0.5318	0.7619	-1.2039

Percentile	0.1		0.2		0.3		0.4		0.5		0.6		0.7		0.8		0.9	
Variable	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
part-time	-0.1491	-0.5673	-0.2400	-0.3829	-0.0848	-0.4806	0.0517	-0.5478	-0.0062	-0.4322	0.1158	-0.5890	0.2316	-0.5526	0.3416	-0.7908	0.3859	-0.8237
	-0.3841	-1.1723	-0.5987	-1.7144*	-0.2872	-2.5223**	0.2207	-2.7494***	-0.0208	-2.3759**	0.3742	-3.3038***	0.6539	-2.6582***	1.0333	-4.2885***	0.9778	-4.6220***
longer than full-time	-0.3861	-0.3923	-0.4492	0.1326	-0.3442	0.2421	-0.2313	0.0501	-0.0036	-0.0371	0.0327	-0.0376	0.0497	-0.1436	0.0583	-0.2530	0.0106	-0.1342
	-1.5827	-0.6719	-1.4586	0.5484	-1.1068	1.8638*	-0.9744	0.4050	-0.0164	-0.2879	0.1752	-0.3152	0.3341	-1.1261	0.3397	-1.3434	0.0441	-0.6120
determinante contract	0.7365	0.5379	0.5704	0.1721	0.2867	-0.0286	0.3302	-0.0118	0.2109	-0.1181	0.1493	-0.2355	0.0842	-0.1592	-0.0467	0.0391	0.1484	-0.0853
	1.9642**	0.7683	1.7474*	0.7603	1.1379	-0.1739	1.4719	-0.0788	1.0235	-0.7807	0.8096	-1.3907	0.5259	-0.7296	-0.2741	0.1329	0.3322	-0.2348
other contract	-0.1024	0.5183	-0.1246	0.6737	-0.2537	0.4565	-0.3041	0.5767	-0.4225	0.7379	-0.3831	0.4560	-0.4489	0.3416	-0.5897	0.0551	-0.5118	0.1843
	-0.2325	0.7933	-0.2718	1.5829	-0.6187	1.7070*	-1.0829	2.1882**	-1.2263	3.0479***	-1.2373	1.7204*	-1.2342	1.0113	-1.8188*	0.1809	-1.1322	0.5835
g	-15.1391	-1.2964	-14.5077	-9.1397	-12.7377	-6.0114	-11.4456	-1.9716	2.0732	-0.0004	6.6905	-0.2341	11.0447	-0.1875	10.4731	2.1501	13.9497	2.2427
	-0.9491	-0.0823	-1.4848	-1.9829**	-1.4347	-1.4861	-1.6594*	-0.2812	0.2963	-0.0001	0.9229	-0.0655	1.6792*	-0.0438	1.5570	0.4979	1.8822*	0.4362
g^2	1.1573	0.1537	1.1840	0.7820	1.0330	0.4951	0.9368	0.1605	-0.1720	0.0313	-0.5561	0.0346	-0.9355	0.0222	-0.8918	-0.1706	-1.2034	-0.1509
	0.8953	0.1114	1.5072	2.1138**	1.4533	1.4387	1.6966*	0.2608	-0.2991	0.1085	-0.9174	0.1197	-1.7098*	0.0647	-1.6052	-0.4947	-1.9621*	-0.3628
g^3	-0.0430	-0.0067	-0.0475	-0.0319	-0.0405	-0.0196	-0.0371	-0.0061	0.0072	-0.0022	0.0226	-0.0021	0.0383	-0.0012	0.0367	0.0064	0.0498	0.0049
	-0.8369	-0.1144	-1.5447	-2.2359**	-1.4708	-1.3900	-1.7266*	-0.2349	0.3119	-0.1985	0.9207	-0.1885	1.737*	-0.0919	1.6501*	0.4840	2.0154**	0.3016
g^4	0.0008	0.0001	0.0009	0.0006	0.0008	0.0004	0.0007	0.0001	-0.0002	0.0001	-0.0005	0.0001	-0.0008	0.0000	-0.0007	-0.0001	-0.0010	-0.0001
	0.7619	0.1107	1.5608	2.3508**	1.4604	1.3393	1.7151*	0.2076	-0.3531	0.2762	-0.9458	0.2514	-1.7820*	0.1176	-1.7050*	-0.4687	-2.0647**	-0.2483
g^5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-0.6788	-0.1050	-1.5583	-2.4631**	-1.4262	-1.2971	-1.6698*	-0.1851	0.4142	-0.3509	0.9858	-0.3164	1.8385*	-0.1502	1.7638*	0.4405	2.1074**	0.1938
Observations:	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003	845	1003
Adjusted R-squared:	0.2304	0.2484	0.2020	0.2241	0.1965	0.2163	0.1876	0.2066	0.1843	0.1980	0.1763	0.2064	0.1816	0.2108	0.1938	0.2198	0.2231	0.2355

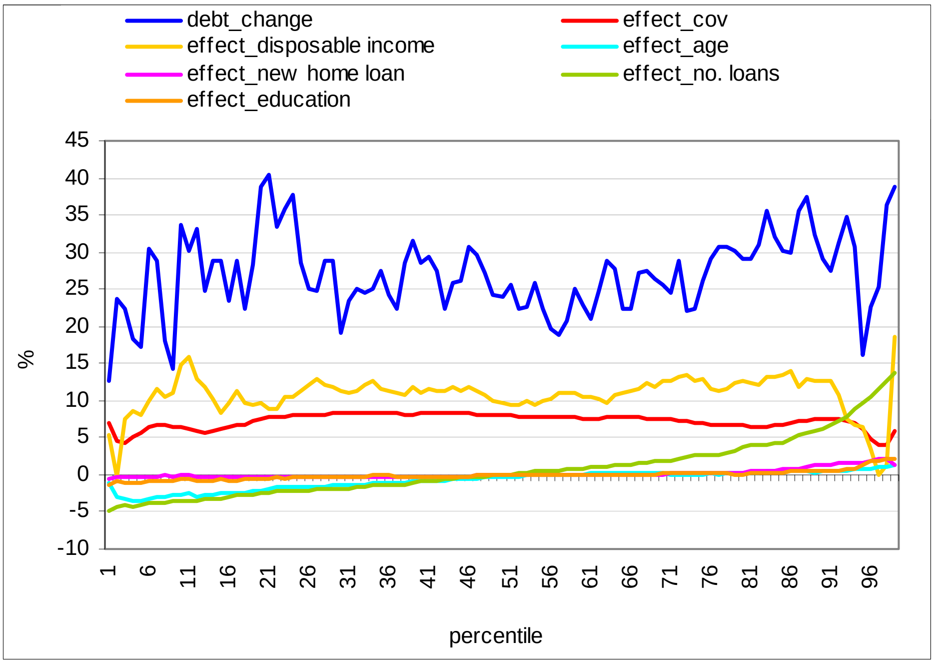
t- statistics is given in the second line.
***, significant at 1% level
**, significant at 5% level
*, significant at 10% level
Source: authors' calculations based on the Household Budget Survey

Figure 3 Machado-Mata decomposition the change in household debt between 2005 and 2008 (without sample selection correction)



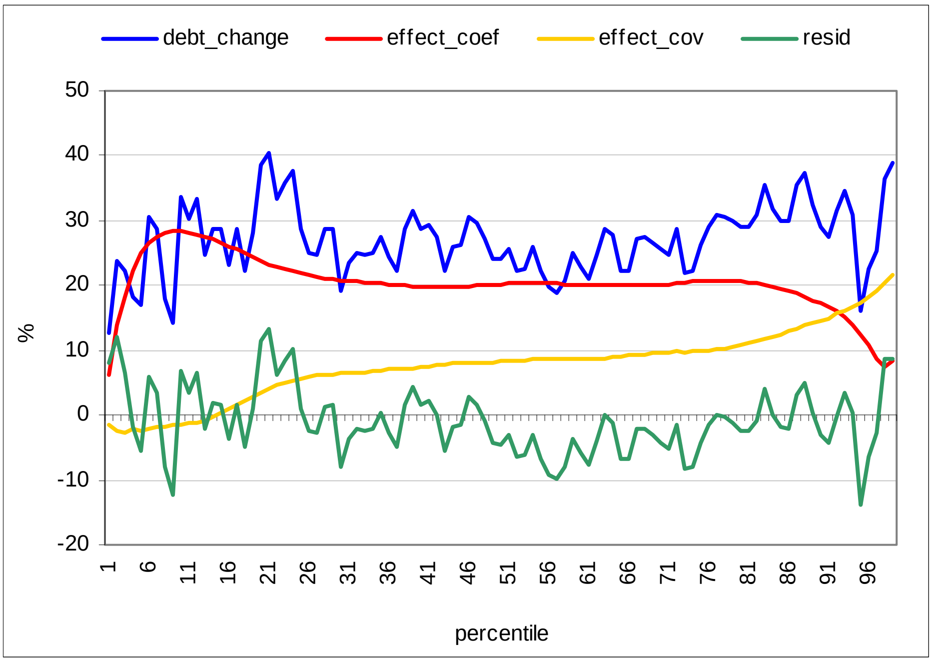
Source: authors' calculations based on the Household Budget Survey

Figure 4 Contribution of individual covariates to the household debt rise between 2005 and 2008 (without sample selection correction)



Source: authors' calculations based on the Household Budget Survey

Figure 5 Machado-Mata decomposition of the change in household debt between 2005 and 2008 corrected for sample selection bias



Source: authors' calculations based on the Household Budget Survey

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