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The Role of Demand and Supply in Cyclical Fluctuations of Household Debt in Croatia

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Abstract

This paper explores whether recent fluctuations of household borrowing in Croatia were primarily caused by the more restrictive banks' lending policies or changes in household demand for loans. A distinctive route is taken compared to previous empirical studies on cyclicality of banks' lending policies as two segments of lending standards are modeled separately: criteria that households should satisfy in order to qualify for a loan and the highest loan amounts banks are willing to approve to the eligible households. Part of the modification in lending standards may therefore be observed in the form of easier or more difficult access to debt rather than change in the average debt level. A two-step methodology is proposed corresponding to these two segments of lending policies. The evidence suggests that in Croatia banks only partially tightened their lending policies through more difficult access to credit, while at the same time the maximum loan amounts made available to credit-worthy households even increased compared to the previous year. Household loan demand therefore had the prominent role in the process of household deleveraging during the observed crisis period.

Introduction

Recent global financial crisis once again proved the notion that "credit lies at the heart of the crisis" (Aikman, 2010). Many economists advocate that during the pre-crisis upswing period of the global economy banks had pursued lenient lending policies which resulted in excessive accumulation of credit risk in balance sheets of the entire spectrum of financial institutions. However, as economic outlook deteriorated and piled-up credit risk materialized, banks tightened their credit policies which further amplified descending path the global economy was on. Therefore, it is not surprising that after the outbreak of the crisis much attention has been directed to the problem of pro-cyclicality in banks' lending standards.

Theory of banks pro-cyclical behaviour is typically associated with Minsky (1992) who noted: "from time to time, capitalist economies exhibit inflations and debt deflations which seem to have the potential to spin out of control. In such processes the economic system's reactions to a movement of the economy amplify the movement-inflation feeds upon inflation and debt deflation feeds upon debt deflation". His financial instability hypothesis suggests that during the "good-times" of economic prosperity, due to optimism and euphoria, financial units are willing to take on more risk which leads to speculative and consequently ponzi finance in which a loan can only be refinanced if the price of the underlying asset increases. However, the eventual burst of the asset price bubbles will decrease collateral value which will in turn increase credit losses and lead to tightening of lending policies and credit crunch.

Apart from Minsky, many other views and models of credit cycles and pro-cyclical bank behaviour that differ with respect to micro-economic frictions which are thought to aggravate credit cycles by acting as financial accelerators (Aikman, 2010), emerged. In related literature pro-cyclicality in banks' lending standards was also associated with: agency cost of lending (Bernanke et al, 1996), capital constraints (Holmstrom and Tirole, 1997), change in the price and value of underlying collateral (Geanakoplos, 2010), strategic behaviour of heterogeneous banks (Rajan, 1994), specifically bank herding (Acharya and Yorulmazer, 2008) or proportion of new loan applications, especially from previously unknown borrowers, that affects adverse selection problem seeming from information asymmetry among lenders and consequently leads to modification of banks lending standards (Dell' Ariccia and Marquez, 2006).

However, some more recent evidence shows that fluctuations in the demand for loans (e.g. those arising from adverse selection among the borrowers due to precautionary demand for loans) rather than supply of loans, may be even more important driver of aggregate household borrowing (Calem et al, 2011). Against such a background, this paper aims to identify whether recent fluctuations of household borrowing in Croatia were primarily caused by the more restrictive banks' lending policies or changes in household demand for loans.

This paper takes a distinctive route compared to previous empirical studies on cyclicality of banks' lending policies (Herrala, 2009) and differentiation of demand and supply effects on the changes in credit growth (Chen and Wang, 2008) that have exclusively relied on stochastic frontiers analysis. Such an approach is inadequate for providing a full picture of credit market developments as it orients solely on available banks' credit limits and at the same time ignores access to credit as an important determinant of banks' lending policies.

Therefore, new approach is proposed that separately models two segments of lending policies: criteria that households should satisfy in order to qualify for the loan and the highest loan amounts banks are willing to approve to the eligible households. Part of the modification in lending standards may therefore be observed in the form of easier or more difficult access to debt rather than change in the average debt level. For this purpose the first step of the analysis will be to estimate the probabilities for existence of loan demand and loan supply for each household in the sample. Since it is possible to identify only indebted households rather than actual demand and supply, a model of partial observability will be employed in this step. In the second step, a potential maximum loan amounts ("banks' credit limit") will be estimated using two different approaches (stochastic frontier analysis and quantile regression) for each indebted household depending on its specific socioeconomic and demographic characteristics. Application of these two steps in conjunction should provide basis for the estimate of change in both segments of lending policies over time - loan accessibility and credit limit.

Application of the presented methodology will help to fully identify the effects that both sides of the household credit market have on the credit contraction. At the same time it will also allow for the separation and identification of impacts from the two inseparable segments of the banks’ lending policies - credit accessibility and loan amount availability.

The paper is organized as follows. The next section describes the methodology used in estimation of causes of household debt decrease between 2008 and 2009. The subsequent section describes the used data set. Empirical results of stochastic frontier analysis and quantile regression approach together with the decomposition of change in household credit limit are given in the penultimate section. The last section concludes.

Methodology

Main objective of this paper is to identify whether the decline in the amount of the newly approved loans and therefore also total household debt after the outbreak of the financial crisis in Croatia was primarily caused by the more restrictive banks' lending policies or to the crisis adapted household demand. A two-step procedure was employed since the modification of the banks' credit policies can be conducted via two segments of the loan approval process: determination of the criterion the household should comply so that the loan could be granted in the first place and/or decision on the maximum loan amount that could be approved to the household that satisfies these loan approving conditions.

The first step in the proposed methodological framework describes the segments of the banks' loan approval process in which criterion for loan approval are defined. By comparing the probability of obtaining bank loan before and after the outbreak of the financial crisis for each household in the sample, we should determine whether banks have tightened their loan approval requirements and made access to credit more difficult. Utilization of the binary dependant variable model provides a methodological framework for estimating credit market participation probabilities. Change in the estimated probabilities for loan existence reflects combined effect of both supply and demand side of the market.

Probability that an individual household is indebted ($L_{it} = 1$), i.e. probability of loan existence, is simply the intersection of demand and supply, $D_{it} = S_{it}$ (Nguyen, 2007). In case of full information availability we should be able to observe the values of both supply (S_{it}) and demand (D_{it}) at level of individual household (i) in a particular year (t). However, household is not indebted ($L_{it} = 0$) in case if there is no incentive from at least one side of the credit market ($D_{it} = 0 \,\&\, S_{it} = 1; D_{it} = 1 \,\&\, S_{it} = 0; D_{it} = 0 \,\&\, S_{it} = 0$). Due to the insufficient information in the used data set[1], only determination of household indebtedness (i.e. L_{it}), rather than actual demand and supply, is possible. Non-existence of full information matrix aggravates the estimation of the probabilities for existence of both sides of credit market. Therefore, partial observability model that addresses the problem of non-observable credit demand and supply was employed.

Partial observability model was first introduced by Poirier in 1980 and is given by:

$$L_{it} = D_{it} * S_{it} \qquad (1)$$

for household $i = 1 \dots n$ at time $t = 1 \dots m$, where L_{it} is observable from the data and denotes if household is indebted ($L_{it} = 1$) or not ($L_{it} = 0$). D_{it} and S_{ij} are dummy variables of household credit demand and bank credit supply. However, since demand and supply are not observable in this analysis, they are represented by the latent variables D_{it}^* and S_{it}^*:

$$D_{it}^{\ *} = \alpha X_{it}^{d} + e_{it} \text{ ; if } D_{it}^* > 0 \Leftrightarrow D_{it} = 1 \qquad (2)$$

$$S_{it}^{\ *} = \beta X_{it}^{s} + \varepsilon_{it} \text{ ; if } S_{it}^* > 0 \Leftrightarrow S_{it} = 1$$

where X_{it}^{d} and X_{it}^{s} denote matrixes of socioeconomic and demographic characteristics of household i that, in order to distinguish demand from supply, differ in at least one variable (the exclusion restriction), α and β are coefficients to be estimated and e and ε are normally distributed error terms.

Partial observability model assumes that the probability distribution of the loan existence (L_{it}) is driven by normally distributed[2] bivariate process representing binary choice of credit demander (household) and supplier (bank). The probability that a particular household i is indebted is therefore given by the joint probability (Aydemir, 2003):

$$\Pr(D_{it} = 1, S_{it} = 1) = \Pr(S_{it} = 1 \mid D_{it} = 1) * \Pr(D_{it} = 1) = \Pr(L_{it} = 1) \qquad (3)$$

Utilization of this model will enable the estimation of both household likelihood of applying for a loan (probability of demand) and probability of bank approving the loan (probability of supply). Comparison of estimated demand and supply probabilities for 2008 and 2009 will

[1] Croatian Household Budget Survey.

[2] Other distributional assumptions about the bivariate process are possible (like logistic, Cauchy or complementary log-log distribution). Demand and supply probabilities estimated from partial observability model were generally robust to these distributional specifications.

indicate changes in the loan accessibility segment of bank lending policies and their effect on the household debt dynamics.

In the second step of the analysis two different approaches were used in order to estimate the segment of the loan approval process in which maximum loan amounts that could be approved are determined. Stochastic frontier analysis (SFA) was employed first since it is a rather standard technique in estimating maximum output that a certain process can produce given available inputs. However, due to several limitations imposed by SFA this approach was supplemented with quantile regression (QR) analysis which eliminates these restrictions.

SFA was primarily developed as a standard production function innovation by including the technical inefficiency term of the production units. The level of the firm's technical efficiency is determined by the relation of the observed and potential production (Green, 1993). If a firm's actual and potential output are equal, the firm is perfectly efficient. However, if the actual output lies below the production frontier, the deviation of the observed from the potential output represents the degree of firm's technical inefficiency.

In a household lending framework, usage of the SFA enables determination of the maximum amount of a loan that a bank is prepared to lend to a certain household in a particular year. This potential maximum loan amount, i.e. credit limit, ($\max(Y_i)$) represents the banks' credit supply and it depends on the household specific socioeconomic and demographic characteristics (X_{ij}) and banks' evaluation of those characteristics (β_j), i.e. implicit banks' credit scoring models and policies, i.e.:

$$\max(Y_i) = \prod_{j=1}^{n} \left(X_{i,j}^{\beta_j} \right) \exp(e_i); \ \exp(e) \text{- standard normal random variable} \tag{4}$$

However, in reality only the realised loan amounts are observable, the potential ones are not, and this fact aggravates direct estimation of credit limits (expressed as in the equation 4). Observable, realized borrowing on the other hand can be perceived as an indicator of household's efficiency in exploiting available credit limits, presented as:

$$Y_i = \exp(-u_i) * \max(Y_i) \tag{5}$$

In this equation, $\exp(-u_i)$ presents the random component indicating used portion of the credit limit, i.e. households loan demand. It is usually characterised by the one-sided empirical probability distribution[3], which may be heteroscedastic and time-variant (Herrala, 2009).[4]

Multiplying both sides of the equation (4) by the efficiency term and inserting equation (5) gives the standard stochastic frontier model[5] which enables indirect estimation of the credit limits:

$$\log(Y_i) = \beta * \log(X_i) + e_i - u_i \tag{6}$$

By employing SFA we are therefore able to determine the maximum potential amount of the loan ($\max(Y_i)$) that the bank is, in accordance to its credit standards and policies (β), willing to approve to the household with certain socioeconomic and demographic characteristics (X_i), based on the observable realized loan amount (Y_i) and household's borrowing efficiency (u_i).

In the presented SFA model the change of the credit limits form 2008 to 2009 will therefore indicate the supply effect, i.e. the change of the banks' credit policies in the segment of loan amounts, while the deviation of the realized loan amounts from the potential ones should show the demand effect on the household debt dynamics.

However, as mentioned before, the SFA approach suffers from several drawbacks. First, it imposes an explicit functional form of the frontier and distribution assumption on the data (Herrero and Pascoe, 2002) which, if misspecified, can bias the estimated results.

Further, it does not allow correction for the sample selectivity bias that may emerge because the analysis is not preformed on a random but on a sample of only indebted households. Selection of households to whom credits are granted crucially depends on households' decision to apply for a bank loan and a banks' decision to approve the loan and it is therefore not random. Yet, the SFA approach will not take into consideration the effect of the changes

[3] Usually exponential, half-normal or truncated normal distribution.
[4] However, in reality distribution of the households' borrowing efficiencies is unknown.
[5] Presented in logs.

in the process of selecting households to which loan will be approved in the first place since it is limited to recognition of only changes in the credit limits segment of the lending policies. That may bias the results if not taken into account.

Finally, the SFA makes it difficult to disentangle the impact of the banks' credit policies changes from the improvement of the households' creditworthiness on the household debt dynamics. Changes of the household creditworthiness will affect the total amount of household debt regardless of the banks' credit policies modifications. It is therefore crucial to separate the contribution of the improved creditworthiness on the debt change in order to correctly identify the supply and demand effect on household debt dynamics.

Due to this reasons, quantile regression (QR) approach (Koenker and Bassett, 1978) is used as an alternative to SFA since it alleviates all mentioned disadvantages imposed by the SFA[6]. It also enables identification and separation of the household credit demand effect and the effect of the lending policies on the entire distribution of the newly granted loans, since it provides a large number of different frontiers corresponding to different quantiles of the conditional distribution of the dependant variable[7]. Quantile regression model is given by (Buchinsky, 1998):

$$y_i = x_i'\beta_\theta + u_{i\theta}$$

$$Quant_\theta(y_i / x_i) = x_i'\beta_\theta, \text{ where } Quant_\theta(u_{i\theta} / x_i) = 0 \text{ and } \theta \in [0,1]^8 \quad (7)$$

where y_i denotes the natural logarithm of the amount of debt carried by the i^{th} household, x_i is a vector of i^{th} household's specific socioeconomic and demographic characteristics, which proxies for its creditworthiness, and β_θ is a vector of estimated coefficients on the θ quantile of the conditional distribution of household loan that approximate for bank lending policies.

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[6] It doesn't imply any distributional assumptions about the inefficiency term (Liu, Laporte and Ferguson, 2007) because it only requires an assumption about the functional form of the frontier and it also allows correction for the sample selection bias and separation of the creditworthiness effect.

[7] For more on the advantages of the quantile regression approach compared to the conventional frontier framework (mainly Stochastic Frontier Analysis and Data Envelopment Analysis) see Liu, Laporte and Ferguson, 2007.

[8] $Qunat_\theta(y_i / x_i)$ represents the conditional quantile of the y_i, conditional on the regressor vector x_i. There are no assumptions about the error term $u_{i\theta}$ distribution; except that it is assumed that error term $u_{i\theta}$ satisfies quantile restriction $Quant_\theta(u_{i\theta} / x_i) = 0$ (Buchinsky, 1998).

While the loan demand most likely has the crucial importance for the amount of household debt at the lower conditional quantiles of the household indebtedness distribution, at the highest conditional quantiles the most important restrictive factor are banks' lending standards, i.e. loan supply. The maximum available amount of a loan for every indebted household in the sample is therefore determined based on the different socioeconomic and demographic characteristics of that household and QR coefficient on those characteristics estimated at the highest conditional quantiles of the newly approved loan distribution. Selection of the quantile which will represent credit limitation imposed by banks' lending standards is arbitrary.

Conjunction of two segments of the lending policies, loan accessibility and credit limits, that together represent loan supply, is possible if sample selection correction, i.e. probability of loan existence, is incorporated into credit limit estimation. This connection will be carried out by adjusting Heckman two-step correction procedure to the used QR framework. Basically, a conditional quantile of the observed amount of household loan will depend on, apart from the household's specific characteristics (x_{it}), the probability for loan existence ($\Pr(L_{it} = 1)$) estimated in the first step of the analysis.

Finally, in order to separate the effect of improved households' creditworthiness from the effect of changed banks' lending policies, Machado-Mata (MM) decomposition technique[9] is used. In this procedure the characteristics of indebted households are used to proxy for their creditworthiness so the changes of estimated quantile regression coefficients could be used to approximate possible tightening of bank's lending standards. Such decomposition allows the construction of counterfactual debt distributions that simulate the evolution of household indebtedness patterns if creditworthiness of indebted households did not change over time. An intuition behind the described approach is that decomposition of changes in indebtedness patterns would allow for objective assessment in banks' lending standards. Machado-Mata decomposition is augmented in such a way to specifically account for the changes in the probability for loan existence. However, this also complicates the decomposition because there is no straightforward way to assign the effect arising from changes in probability that

[9] The Machado-Mata decomposition is widely used in the literature on wage inequality, for which it has been primarily developed (see Machado and Mata, 2005; Albrecht et al, 2008; Nestić, 2010 etc.)

household will be willing to take on debt and changes in banks' selection of creditworthy households[10].

Data

Analysis was performed on the micro data from the Households Budget Survey (HBS)[11] which contains detailed data on income, wealth and most household consumption expenditures. Apart from the household-level data on income and expenditures, HBS also gives insight into socioeconomic and demographic characteristics of surveyed individuals.

For the purpose of this paper's research the HBS for years 2008 and 2009 were used. This was a period of financial crisis culmination which may have altered household borrowing patterns and banks' lending policies by making them less expansive. These possible changes in household borrowing and lending attitudes were reflected in decrease of the newly granted loans and accumulated household debt during this period.

The analysis was preformed on the sample of newly indebted households, i.e. households to whom a new loan was extended to in a particular year, regardless of the loan type. Orientation on only newly approved loans during last twelve months instead of on all loans regardless of their "age" is essential since it allows for isolation and identification of the banks' lending standards prevailing in only one specific year. The estimation of the probability for loan existence was performed on the whole sample of surveyed households. The dependant variable in probability model is a binary variable that equals 1 if household obtained some type of bank loan in the observed year and 0 if not. Dependant variable used in the SFA approach and QR equations is the natural logarithm of the observed total amount of newly taken household loan.

Table 1 gives some descriptive statistics for the whole sample of surveyed households in both observed years and two sub-samples: indebted households regardless of the time when they took the loan and households with bank loan taken during the last year, i.e. newly indebted households. Characteristics of the newly indebted households in both years remained quite

[10] More on MM decomposition and possible treatments of the selectivity effect in the quantile regression is available in Ivanov (2008).
[11] HBS is conducted annually by Central Bureau of Statistics (CBS). For more details on HBS see CBS, 2010.

similar. During this period banks were usually granting loans to the middle aged, married male that owns a home in the urban area and on average has less then one child. He is middle educated, works usually in private or public company dealing in tertiary sector of economic activity and has a permanent working contract on full-time working hour. However, the most significant change of household credit financing between 2008 and 2009 is observable in the type of newly granted loans. In 2009 less then 4% of all newly granted loans in our sample were home loans that in previous year accounted for 13% of all new credits. This is in line with aggregate data on household lending that shows a considerable downsizing in the amount of newly approved long-term loans during crisis (see Figure 1 in Appendix) and with negative trends (turnover decrease and fall of price) that prevailed on real estate market since the end of 2007, possibly implying that households accommodated to the financial crises by orienting more on the smaller loan amounts which will not burden their financial situation for a long time.

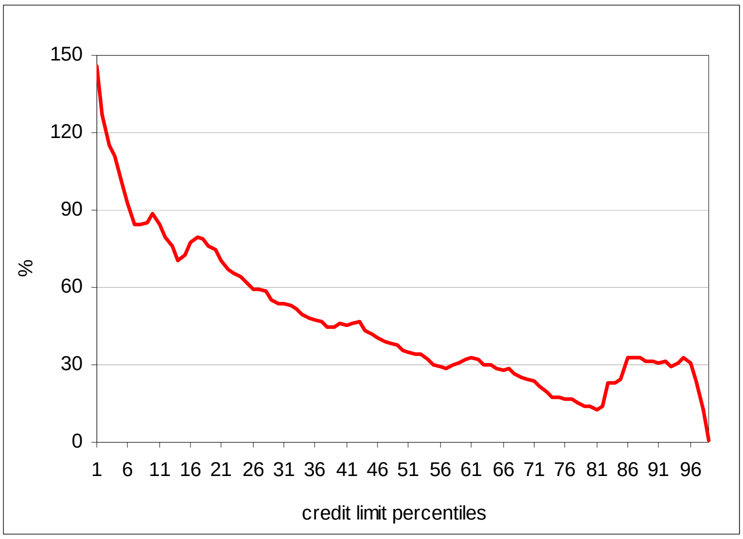
In 2009 only 9.2% of all households took a new bank loan which is two percentage points less compared to the previous year. This could indicate that as the financial crises culminated, banks' loans were made less available to households or that possibly households accommodated their borrowing patterns by postponing new borrowing for "better times" when the economy recovers. At the same time the average amount of newly granted loans also decreased by some 3.5%. Therefore, apart from the loan accessibility, as a reaction to the crises banks may have also reduced the loan amounts available to households who they assess as credit-worthy.

Results

1. Estimation results from the SFA approach

The SFA approach conducted on the micro data from HBS for years 2008 and 2009 shows that, in spite of the strengthening of the financial crisis, in 2009 banks have actually increased supply of new household loans compared to the previous year. The biggest increase of the banks' loan supply is observable in the segment of smaller loan amounts, decreasing with the rise of the maximum loan amount which is in accordance with the aggregate data.

Figure 1 Change of estimated household credit limits between 2008 and 2009



Source: author's calculation based on the HBS

From the large set of household's characteristics that may affect household's loan repayment capability, the disposable income, age of the household's head and level of education which proxy for future income perspective are the only statistically significant explanatory variables in estimated frontiers (see Table 2 in Appendix). As expected, the frontier, i.e. banks' loan supply in both observed years, increases with the amount of the household's current disposable income. The effect of the age of the household's head on the maximum available loan amounts is consistent with the theoretical life-cycle model of consumption, with young households taking on more debt. In 2009 the level of education of household's head also proved to have significant impact on the banks loan supply, indicating that banks are more willing to offer higher loan amounts to households with better prospects for future income growth.

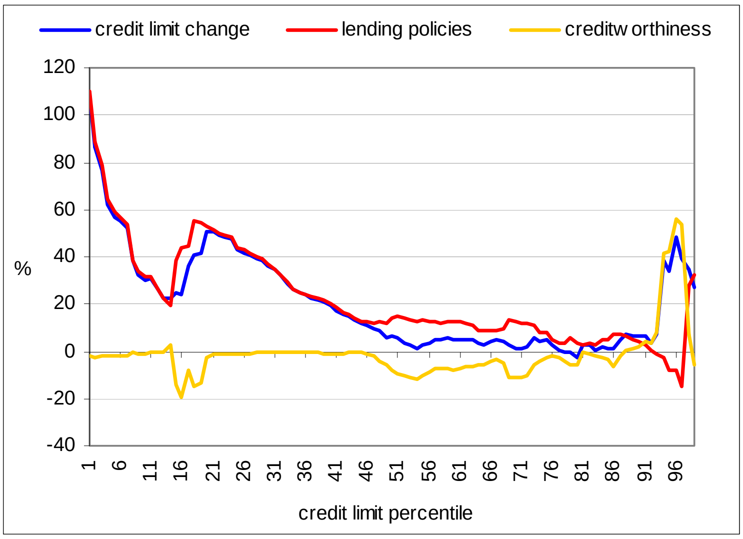
2. Estimation results from the QR approach

Due to the mentioned limitations of the SFA approach, changes in household lending/borrowing patterns were also assessed employing quantile regression framework. Credit limits were determined using different households' characteristics and coefficients on those characteristics estimated at the 80th percentile. Credit limit in 2008 determined using coefficients estimated on 80th percentile on average trace SFA limits very well. However, in

2009, the usage of the 90th percentile is more appropriate[12]. For the purpose of further analysis it is essential that for both observed years credit limits are determined using QR coefficients estimated on the same percentile so the 80th percentile was arbitrarily chosen[13].

As mentioned before, change in the volume of available household loans can be a consequence of improved characteristics and better loan repayment capability of households that applied for the loan in a particular year, rather than expansive banks' lending policies. For this reason, shift of the banks' credit limits between 2008 and 2009 was decomposed into a part attributable to the alteration of households' creditworthiness (approximated by households' characteristics) during this period and a part that represents the possible modification of banks' lending standards (approximated by estimated QR coefficients) using previously described Machado-Mata decomposition technique.

Figure 2 Decomposition of credit limit change between 2008 and 2009



Source: author's calculation based on the HBS

Estimation results from the quintile regression approach support the concussions drawn from the SFA. They show that in 2009 banks increased offered credit limits compared to those provided in 2008. Increase of loan supply was especially pronounced in the segment of smaller loan amounts. On average banks' credit limits grew by some 21.1% during the observed one year period.

[12] Credit limits were also estimated on 82.5th, 85th, 87.5th, 90th, 95th and 97.5th percentile.
[13] All further analyses whose results using 80th percentile are presented in the paper, were also carried out using coefficients from the 90th percentile. The results and conclusions derived from them are the same.

Further, MM decomposition suggest that observed increase in the maximum loan amounts was primarily caused by the more lenient banks' lending policies contributing to the overall rise of credit limits by some 23 percentage points. At the same time creditworthiness of households' that obtained some type of bank loan during this period actually deteriorated, with negative impact on credit limit dynamics averaging to -1.4%.

Both the SFA and the QR analysis indicate that the credit limits generally increased between 2008 and 2009, with decreasing rise of credit supply in relation to the loan size. However, as mentioned before, available loan amounts represent only one segment of banks' lending policies that can provide a full picture of banks lending behaviour only if it is taken into account together with the likelihood of a loan being approved in the first place.

Probabilities of loan demand and loan supply existence were estimated using the model of partial observability. For the purpose of separating and identifying loan demand and supply, various combinations of variables on both market sides were used[14]. On the demand side dummy variable identifying households that have financial difficulties in servicing living costs had the highest explanatory power and expected (positive) sign in both observed years, while fixed-term working contract variable, dummy variable indicating households that have invested in life insurance and dummy variable identifying previously taken loan were used as identifiers on the supply side on which they have positive effect.

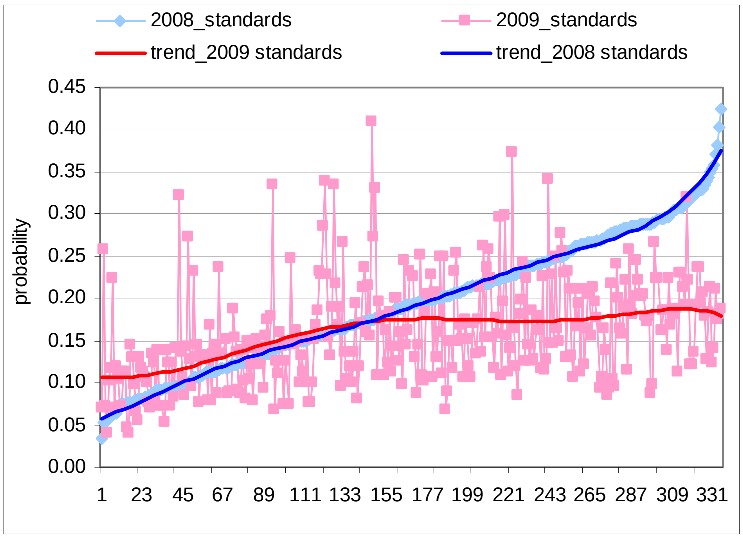
If characteristics of households that obtained bank loan in 2008 are inserted in equation that estimates probability of loan demand and supply with coefficients approximating loan accessibility estimated on 2009 sample, probabilities for loan existence would on average be 5 percentage points lower compared to the previous year. For the sample of households that took loan in 2008 the average probability of demand in that year was therefore 19.4%, decreasing to 16.0% in 2009.

However, a look at the distribution of demand probabilities shows that in 2009 the probability of positive demand actually increased for households which in 2008 had the lowest probability of wanting to borrow. These results could indicate that the slowdown of the

[14] On the demand side variable identifying number of children, number of household members, child birth, amount of remittances and rural area of residence were also tested, whereas rural area of residence, home ownership, existence of prior bank loans and marriage were used to identify household loan supply.

Croatian economy in the last quarter of 2008 and recession that followed in 2009 deteriorated most households' financial situation even though the impact on their borrowing pattern was different. Households that had low propensity to borrow in 2008 because they had none or very little need for additional funding were in 2009 necessitated to lean more on bank loans possibly due to precautionary motives or to bridge over temporary fall of current income below their expected "normal" earnings. In literature this type of household's reaction to deteriorating economic conditions is called pre-emptive borrowing (Calem et al, 2011) and is consistent with the permanent income hypothesis (Friedman, 1957) since households borrow more not as much to increase their current consumption but to ensure their access to liquidity in the future and preserve their purchasing power. On the other hand, borrowing propensity for households that had higher probability of demanding bank loans in 2008 decreased in 2009, which is in line with neoclassical consumption theory that suggests that as consumer expectations of future unemployment rises, expected lifetime wealth will decline, and consumption should fall (Calem et al, 2011).

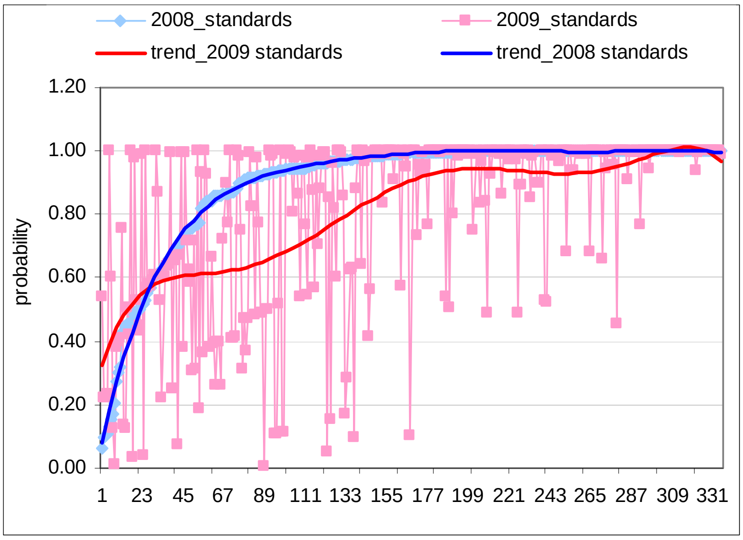
Figure 3 Probability of household loan demand for 2008 sample of households with respect to lending standards in 2008 and 2009



Source: author's calculation based on the HBS

Probability of loan supply existence also decreased during this period, from average 0.90% in 2008 to 0.81% in 2009. Presented results suggest that households that took a bank loan in 2008 would face greater difficulties in obtaining a loan in 2009 due to combination of both supply, i.e. more rigorous banks' loan approving standards in household selection process, and demand, i.e. impaired households' propensity to borrow.

Figure 4 Probability of household loan supply for 2008 sample of households with respect to lending standards in 2008 and 2009

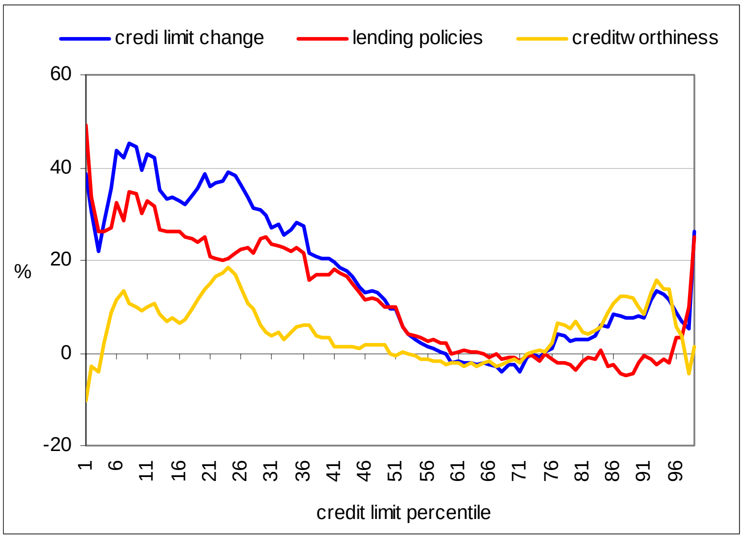


Source: author's calculation based on the HBS

Finally, in order to combine both segments of loan approval process, MM decomposition of changes in banks credit limit which includes estimates of the probabilities for loan demand and supply existence was also employed. Quantile regression framework enables three possible placements of the contribution of the probabilities for the loan existence to the household debt change in MM decomposition: as a part of the characteristics effect (households' creditworthiness in this paper), part of the coefficient effect (banks' lending standards) or it can be excluded from decomposition altogether (Ivanov, 2008). For the purpose of this analysis demand and supply probabilities will be combined together with the banks lending policies[15]. This decomposition is more appropriate if it is believed that the change in the sample selection bias, i.e. probability that household is indebted, arises from differences in the lending standards and household propensity to borrow rather than from the change in characteristics of households which borrow.

Figure 5 Decomposition of credit limit change between 2008 and 2009 that includes probability of loan existence

[15] Results based on the other two possible decompositions are available from the author upon request.



Source: author's calculation based on the HBS

Figure 5 shows that even when the probability for loan existence[16], i.e. household indebtedness, is included in MM decomposition, bank credit limits offered to households increased in 2009 in spite of the recession, whereas creditworthiness of the households to whom loans were granted in 2009 generally improved compared to the 2008 sample.

Presented analysis indicates that in 2009 banks have tightened their lending standards and made access to credit more difficult[17], which points to their pro-cyclical behaviour. However, at the same time they also acted counter-cyclically since on average they offered higher maximum loan amounts to those households that they perceived to be credit-worthy. Taken together with observed increase in creditworthiness of household that were able to obtain loan in such circumstances, these results could imply that during the recession banks have fled to quality (Bernanke et al., 1996) in order to decrease risk exposure of their credit portfolio.

In spite of the credit limits' rise, in 2009 they were used less compared to 2008, as suggested by grater deviation of realized loan amounts from the maximum, potential ones (Figure 7). This proves that as a reaction to recession, households changed their consumption patterns that led to reduced reliance on bank lending and consequently to household delevraging, evident in the drop of new borrowing and total household debt.

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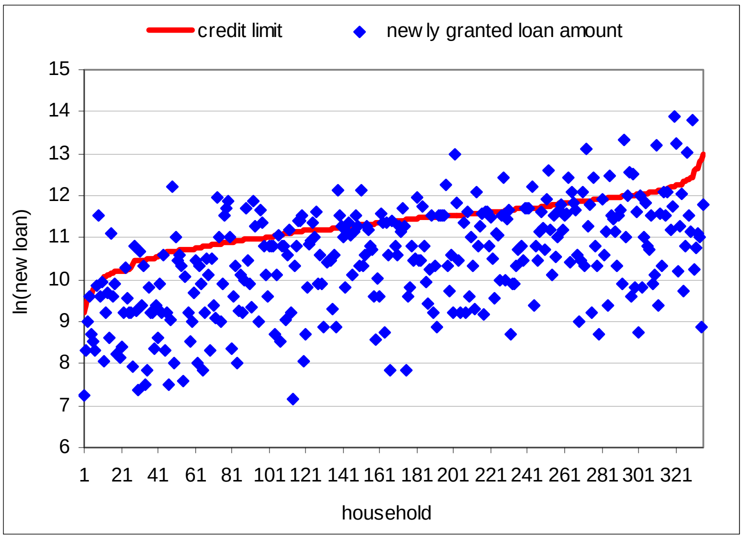
[16] This is the product of probability of loan demand and supply existence.
[17] The same conclusion is derived if characteristics of households indebted in 2009 were inserted in equation that estimates probability of loan demand and supply with coefficients estimated on 2008 sample. On average, their probability of borrowing increased in 2008 indicating more lenient banks' credit standards before the crisis.

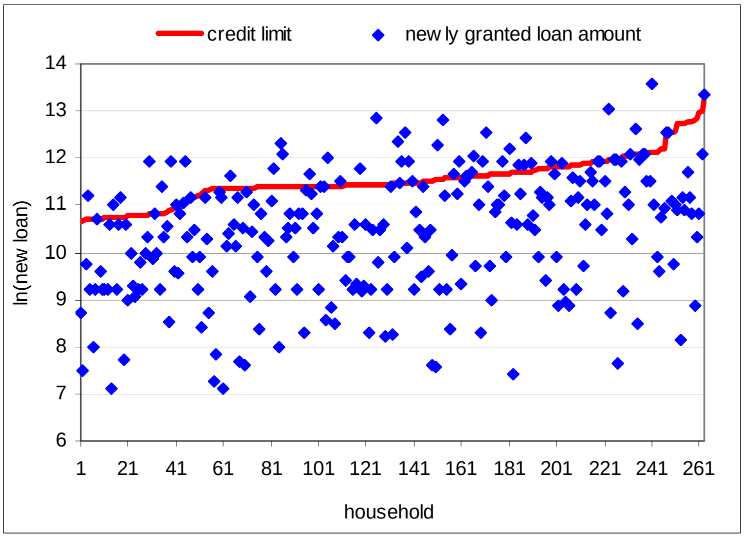
Figure 6 Usage of available credit limits in 2008



Note: Standard deviation is 1.082

Source: author's calculation based on the HBS

Figure 7 Usage of available credit limits in 2009



Note: Standard deviation is 1.251

Source: author's calculation based on the HBS

Conclusions

This paper proposes a rather novel approach to identifying the demand and supply effects on the household credit market dynamics in Croatia that followed after the outbreak of the global financial crisis in the late 2008. In order to determine whether the banks acted pro-cyclically during this recession period and further contributed to the economic slowdown, methodological framework that combines together two crucial aspects of banks lending policies - credit accessibility and loan amount availability - was employed. In the first step of the proposed approach partial observability model was used in order to estimate probabilities for existence of loan demand and loan supply. In the second step of the analysis the probabilities estimated in the first step were incorporated in estimation of the offered credit limits by the means of quantile regression. Utilization of this methodology should be helpful in filling holes immanent to commonly used methods for estimating credit policies pro-cyclicality since correct identification of the causes of loan declines has important implications for policies aiming at restoring or perhaps further diminishing credit momentum.

In 2009 the Croatian economy was marked by recession, unfavourable labour market trends and burst of the bubble in domestic real estate market and capital market that started to erode households' balance sheets. As a reaction to these adverse economic developments banks only partially tightened their lending policies. This pro-cyclical behaviour was principally conducted via process of household selection, while at the same time the maximum loan amounts made available to credit-worthy households even increased compared to 2008. Also, households that were willing and able to obtain a bank loan in 2009 generally had better repayment capability and creditworthiness than household that took loan in 2008. Nevertheless, due to relatively smaller exploitation of the available credit limits, i.e. contraction of the credit demand, there was a considerable drop in the amount of newly granted household loans and total household debt in 2009. This result suggests that household demand had the prominent role in cyclical fluctuations of household debt.

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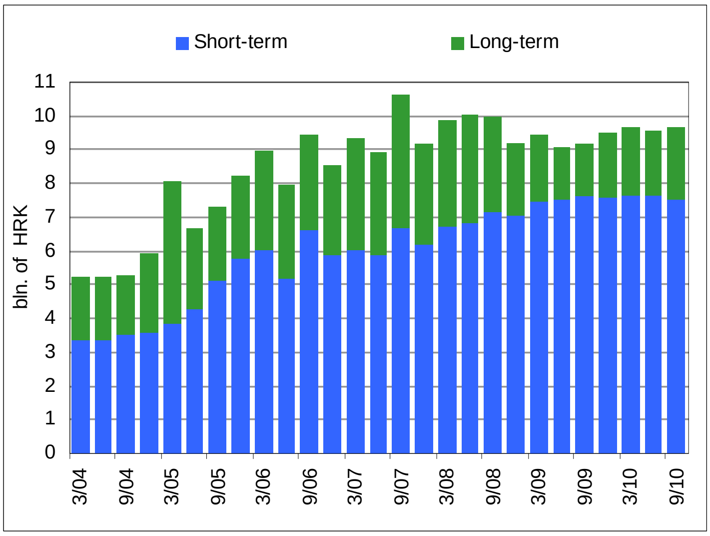
Appendix

Figure 1 Maturity break down of newly-granted household loans



Source: Croatian National Bank

Table 1 Descriptive statistics

Indicator	Observations / Variable	Sample of households: total 3010 2008	total 2864 2009	indebted 1003 2008	indebted 864 2009	newly indebted 336 2008	newly indebted 263 2009
Mean	Disposable income*	77.973,37	81.913,19	104.640,06	111.014,34	103.680,54	107.493,77
	Total Loan*	38.254,92	34.732,04	114.802,90	115.130,28	107.117,18	109.411,42
	New loan*	7.908,99	6.276,83	23.734,86	20.806,54	70.851,38	68.353,04
	No. employed members	1,09	1,11	1,58	1,63	1,60	1,60
	No. children	0,50	0,46	0,74	0,79	0,74	0,75
	No. loans	0,45	0,40	1,35	1,32	1,48	1,48
%	<30	2,66	3,21	2,49	3,24	2,98	7,22
	30-39	7,74	8,76	10,57	14,70	12,50	14,45
	40-49	17,81	17,00	27,82	27,08	27,38	29,28
	50-59	23,29	23,01	29,71	29,05	28,27	25,10
	60-69	21,56	19,17	18,15	16,44	17,86	15,59
	>70	26,94	28,84	11,27	9,49	11,01	8,37
	Male	67,28	67,11	74,18	75,69	75,00	70,72
	Female	32,72	32,89	25,82	24,31	25,00	29,28
	Homeowner	88,57	88,48	89,23	87,85	85,12	84,79
	Renter	11,43	11,52	10,77	12,15	14,88	15,21
	New housing loan	1,46	0,35	4,39	1,16	13,10	3,80
	Single	6,84	7,65	4,09	4,28	2,98	4,94
	Widow	24,82	25,24	13,36	12,73	12,20	12,93
	Married	62,56	61,70	76,77	78,13	78,87	77,95
	Separated	5,78	5,41	5,78	4,86	5,95	4,18
	Education_low	36,48	35,13	20,84	22,57	22,02	22,43
	Education_middle	50,13	50,94	60,92	61,46	59,52	66,92
	Education_high	13,39	13,93	18,25	15,97	18,45	10,65
	Entrepreneur	4,78	4,26	4,59	3,82	3,27	1,90
	Farmer	8,54	7,23	6,98	4,28	5,65	3,80
	Public company	13,59	13,30	24,33	22,34	29,76	22,05
	Private company	17,44	19,41	25,72	30,79	26,49	35,74
	Retired	46,45	46,54	32,40	32,18	31,55	29,66
	Other_works	1,89	1,85	1,40	1,85	0,60	1,52
	Other_doesn't work	7,31	7,40	4,59	4,75	2,68	5,32
	Economic activity sector_primary	22,84	8,66	9,17	6,13	9,23	5,70
	Economic activity sector_secundary	30,39	15,12	20,84	23,61	21,73	26,62
	Economic activity sector_tertiary	46,77	76,22	69,99	70,25	69,05	67,68
	Contract_permanent	90,09	95,32	97,11	96,41	97,32	96,20
	Contract_fixed-term	3,69	2,13	1,40	2,31	2,08	3,42
	Contract_others	6,22	2,55	1,50	1,27	0,60	0,38
	Working time_full	76,64	91,13	91,33	93,52	91,96	94,30
	Working part-time	13,23	4,61	3,89	2,31	3,57	1,14
	Working longer than full-time	10,05	4,26	4,79	4,17	4,46	4,56

Notes:
* In Croatian Kuna (HRK)
Source: author's calculation based on the HBS

Table 2 Estimation results for the SFA

	2008					2009				
	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z	
c	1.04	1.42	0.74	0.46		10.84	0.88	12.34	0.00	***
log(disposable income)	0.89	0.12	7.51	0.00	***	0.08	0.07	1.26	0.21	
<30	0.67	0.36	1.85	0.06	**	0.68	0.31	2.23	0.03	**
30-39	0.56	0.20	2.76	0.01	**	0.11	0.25	0.44	0.66	
40-49	0.37	0.16	2.34	0.02	**	-0.01	0.20	-0.06	0.95	
>60	-0.07	0.18	-0.37	0.71		-0.05	0.23	-0.20	0.84	
low_education	-0.21	0.16	-1.31	0.19		-0.49	0.19	-2.64	0.01	***
high_education	0.17	0.16	1.09	0.27		0.46	0.24	1.87	0.06	**
renter	-0.20	0.18	-1.14	0.25		0.17	0.21	0.80	0.43	
public comp.	0.08	0.16	0.49	0.62		0.19	0.20	0.95	0.34	
enterpreneur	0.50	0.35	1.44	0.15		0.66	0.52	1.25	0.21	
other_works	-0.02	0.39	-0.06	0.95		0.16	0.45	0.36	0.72	
other_doesn't work	-0.19	0.22	-0.86	0.39		-0.20	0.25	-0.81	0.42	
primary activity	0.16	0.34	0.47	0.64		0.11	0.45	0.25	0.80	
secundary activity	-0.10	0.17	-0.56	0.57		-0.02	0.20	-0.10	0.92	
sigmaSq	1.86	0.44	4.23	0.00	***	3.39	0.52	6.55	0.00	***
gamma	0.64	0.19	3.31	0.00	***	0.87	0.06	14.02	0.00	***
log likelihood value	-491.462					-420.575				
mean efficiency	0.498776					0.374954				

Notes:
***, significant at 1% level
**, significant at 5% level
*, significant at 10% level
Source: author's calculation based on the HBS