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WHAT ARE THE
TRIGGERS FOR
ARREARS ON DEBT? EVIDENCE FROM QUARTERLY PANEL DATA


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# What are the Triggers for Arrears on Debt? Evidence from Quarterly Panel Data 

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#### Abstract

The paper investigates the triggers of arrears on debt in Estonia, which is a full recourse country similar to other euro area countries. An extensive individuallevel quarterly panel dataset enables quarterly debt repayment problems to be tracked while controlling for individual specific heterogeneity. The estimations show that lower income and higher debt service ratios are associated with a higher probability of arrears, confirming the "ability to pay" hypothesis. Newly taken consumer loans increase the probability of arrears and the relationship is stronger for loans granted during a recession when credit conditions were tight. Newly taken housing loans exhibit a lower probability of arrears and the same applies to loans granted during the period of easy credit conditions and high real estate prices. The results suggest that the most efficient measures for addressing arrears on debt would be those that mitigate income declines and the debt servicing burden.


JEL Codes: D12, D14, G21
Keywords: arrears, income decline, the debt service ratio, housing loans, consumer loans

The views expressed are those of the author and do not necessarily represent the official views of Eesti Pank or the Eurosystem.

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## Non-technical summary

European countries experienced rapid growth in household credit in the first half of the 2000s when the aggregate debt-to-income ratio of the household sector increased in the euro area by 19 percentage points and debt reached 92 per cent of yearly income in 2007. Estonia exhibited more profound debt accumulation as the debt-to-income ratio grew from the very low level of 15 per cent in 2000 to 88 per cent in 2007.

The 2008-2009 recession was followed by increased vulnerability among households, which resulted in the increase in arrears. The European Survey on Income and Living Conditions (EU-SILC) reveals that the share of households that reported being in arrears on mortgage or rent payments in the last 12 months peaked at 4.6 per cent in the euro area in 2010 while the share was somewhat lower in Estonia at 2.7 per cent. The share of households in arrears on hire purchase instalments or other loan payments reached 3.1 per cent in the euro area while the share was 4.7 per cent in Estonia. The reasons behind the rise in arrears on debt in Europe are underexplored and this paper contributes to filling this gap.

There are two leading theories explaining debt payment problems and default, the "equity" theory of default and the "ability to pay" theory of default. The "equity" theory holds that default is a strategic option for households and the "ability to pay" theory suggests that households will fall into arrears if their income flow is not sufficient to meet their commitments. European countries are mainly full recourse countries, so the ability to pay is expected to play a major role in the repayment behaviour of households. There is evidence that labour market shocks are important factors for explaining arrears or default in European countries.

The purpose of this paper is to provide additional evidence from Estonia, a euro area country with full recourse loans. The paper focuses on income and debt-related variables as potential triggers for debt repayment problems. Micro-level panel data is used from 2005:Q42011:Q4 to explain the role of idiosyncratic shocks that are independent of macroeconomic factors. The fixed effects model is estimated to control for the unobserved heterogeneity. The estimations have been carried out for different sub-samples and business cycle periods. The estimations reveal that an income decline and the debt service ratio are important triggers for arrears, confirming the "ability to pay" theory.

Estimations for different income quintiles show that the probability of arrears is most sensitive to an income decline and to the debt servicing burden in the lowest income group. The probability of arrears is insensitive to the debt service ratio in the highest income group and in this group the arrears are driven by the balance of consumer loans instead, suggesting strategic behaviour by individuals in the highest income group. The results from different business cycle periods indicate that the effect of the debt service ratio and of liquid assets is stronger during the recession, while the role of consumer loans in inducing arrears increased after the recession.

Further estimations indicate that a new or additional housing loan is associated with a lower probability of arrears. Moreover, the estimations reveal that loans taken in 2006-2007 exhibit a lower probability of arrears. Although this period was accompanied both by easier credit conditions and by high house prices, individuals did not tend to fall into arrears.

A different picture emerges for consumer loans, as the probability of arrears is markedly higher in the quarter when a consumer loan is granted, suggesting that consumer loans have been used to alleviate financial difficulties. The evolution in the probability of arrears cannot be explained by the change in credit conditions as the loans granted under a strict credit policy in 2008-2011 exhibit a higher probability of arrears than loans granted in 2005-2006, when credit conditions were relaxed.

The results of the paper indicate that an important way to address the issue of debt repayment problems is to alleviate negative income shocks and the debt service burden. One of the main measures for alleviating income shocks is self-insurance by accumulation of liquid assets, but the results show that this measure does not play any significant role in preventing arrears. Therefore measures which mitigate the debt service burden, such as lowering interest rates or rescheduling loan payments, are more efficient in tackling arrears on debt.

## Contents

1. Introduction ..... 5
2. The model specification ..... 7
3. Dataset and descriptive statistics ..... 9
4. The estimations ..... 14
4.1. Estimations on the full sample ..... 14
4.2. Estimations by income quintiles ..... 16
4.3. Estimations by years. ..... 19
4.4. The probability of arrears for new loans ..... 20
4.5. Does it matter when a new loan is granted? ..... 22
5. Conclusions ..... 24
References ..... 26
Appendix ..... 29

## 1. Introduction

Although there is a wide strand of literature exploring the relationship between nonperforming loans (NPL) and macroeconomic or bank-specific factors, there are only a few studies that explore the triggers of arrears in European countries. Extensive micro-level data are needed to explain the role of idiosyncratic shocks that are independent of macroeconomic factors. The current paper aims to fill the gap by focusing on income and debt-related variables as potential triggers for debt repayment problems. The paper uses an extensive quarterly individual level dataset, which makes it possible to control for unobserved indi-vidual-specific characteristics and to investigate the triggers over time.

There are two leading theories explaining debt payment problems and default, the "equity" theory of default and the "ability to pay" theory of default. The "equity" theory holds that default is a strategic option for households. Borrowers base their decision to default on a rational evaluation of the costs and benefits of continuing or discontinuing debt payments. The equity theory is relevant for non-recourse loans, which are mainly offered in the US, as this type of loan provides incentives to default (Ghent and Gundlyak, 2011).

The second hypothesis, the "ability to pay" theory, suggests that households will fall into arrears if their income flow is not sufficient to meet their commitments. The trigger event for default is an income shock, but only liquidity constrained households fall into arrears; households that are not liquidity constrained continue with debt repayments by using accumulated or borrowed funds to smooth the income flow. European countries are mainly full recourse countries, so the ability to pay is expected to play a major role in the repayment behaviour of households (Bardhan et al., 2011).

Several studies on the US find that negative equity is an important predictor of default while a negative income shock has a negligible effect; see the most recent studies by Bhutta et al. (2011) and Goodman et al. (2010). However, Foote et al. (2008) find that negative equity cannot be the main trigger event as the majority of people with negative equity do not default. Additionally, the studies mentioned use the regional unemployment rate as a proxy for an income shock as they have no individual-specific data. Gyorko and Tracy (2013) use simulations to show that the aggregate unemployment rate is a bad proxy for idiosyncratic income shocks and the results with the unemployment rate severely underestimate the role of income shocks in any default.

Gerardi et al. (2013) is one of the few studies to use unemployment information on an individual level. They exploit the Panel Study of Income Dynamics (PSID) and find that being unemployed is a strong predictor of mortgage default. The impact of severe negative equity on default declines significantly in magnitude when liquid asset positions are taken into account. They claim that strategic default is not a major factor in explaining mortgage default decisions in the US. The studies using loan-level data from LoanPerformance covering US subprime mortgage loans suggest that both the decline in house prices and credit easing contributed to the increase in defaults in 2006 and 2007 (Bajari et al., 2008; Haughwout et al., 2008; Bajari et al., 2013).

There are a few studies which use European data to explore default decisions. Most of the studies explore the characteristics of households with debt arrears before the credit boom in the 2000s. Böheim and Taylor (2000) and May and Tudela (2005) use the British Household

Panel Survey (BHPS) from the 1990s to find that unemployment is a stronger predictor of default than negative equity is, while the debt service burden is an important household-level factor associated with mortgage repayment problems. Similarly, Duygan-Bump and Grant (2008) use the European Community Household Panel (ECHP) from 10 European countries in the 1990s and find that arrears result from adverse shocks such as unemployment. Beckmann et al. (2013) use data from the Euro Survey project of the Austrian Central Bank from nine Central and Eastern European countries (CEEC) from 2010 and 2011. They focus on the role of depreciation in arrears on foreign currency loans and find that income decline has a stronger impact on arrears than exchange rate changes do.

The studies on default are limited because the prevalence of defaults or debt repayment problems is low and the sample that has experienced debt arrears is usually very small. Furthermore, there is a lack of data over the time period and therefore it is not possible to take individual level heterogeneity into account, though it appears to be present. These limitations make it harder to investigate the triggers of arrears with survey data. However, the problems can be solved by using administrative datasets.

There are not many studies from Europe that use register data to investigate the arrears on debt after the 2008-2009 recession; most of the few studies focus on Ireland, which introduced limited recourse contracts in 2010. Lydon and McCarthy (2013) use a loan-level dataset from the Irish banks at the end of 2010. They estimate that the loan-to-value ratio and high repayment burden are related to a higher probability of arrears. They use the regional unemployment rate to capture the effect of negative income shocks on arrears. McCarthy (2014) combines cross-sectional survey data with data from financial institutions from 2012 in Ireland to assess the role played by the unfavourable labour market conditions and by negative equity in the mortgage arrears crisis. McCarthy (2014) shows that both unemployment and negative equity have been key drivers of arrears. Connor and Flavin (2015) use an Irish cross-sectional sample of troubled mortgage accounts and find that in the sample the loan-to-value ratio, the debt service ratio and negative income increase the probability of default.

Mocetty and Viviano (2014) is the only study in Europe that uses panel data. They use Italian register data, annual tax records and unemployment records from 2004 to 2011, and investigate the role of income decline and unemployment in default. They confirm that job loss is a strong predictor of default.

The short literature list shows that the reasons for default after the period of extensive debt accumulation in the 2000s in Europe are underexplored. The studies which use survey data accept that the debt arrears are assumed to be under-reported as the arrears are self-reported (Duygan-Bump and Grant, 2008). When register data are used, the measurement error from under-reporting is eliminated. But in turn, the information about other features beyond those related to loan contracts is very limited. There is evidence that labour market shocks are important factors for explaining arrears or default in European countries. The purpose of this paper is to provide additional evidence from a euro area country.

This paper contributes to the literature in several ways. First, the dataset contains information on both the balance sheet components and the income of individuals, so different triggers for arrears can be compared. The use of individual income instead of a proxy labour market status or the regional unemployment rate addresses the issue of measuring idiosyncratic
shocks. Second, most studies focus on one loan type, such as mortgages or credit cards, and there is no information about the repayment behaviour for other types of loans. In this paper we take a holistic view of the individual's debt repayment behaviour, including information on both housing and consumer loans. Third, the paper uses quarterly panel data, which lets us track the repayment behaviour of the same individuals over 29 quarters. The extensive dataset allows us to explore triggers of arrears in different sub-samples and in different time periods. Additionally, it is possible to investigate the development of the probability of arrears for different types of loans over a business cycle.

The paper proceeds as follows. Section 2 looks at the potential determinants of arrears and introduces the empirical model. Section 3 presents the dataset and analyses the development of the main variables over the sample period. The estimations for different model specifications, business cycle periods and sub-samples are provided in Section 4. Section 5 concludes the findings.

## 2. The model specification

In theoretical models the option of defaulting is derived from a household's optimisation problem. A borrower maximises the intertemporal expected utility with the given budget constraint. The borrower decides to default when the expected benefit from reneging on the debt is higher than the cost of the expected sanctions, including reduced credit availability and higher interest rates in the future. In a non-recourse economy negative equity provides an incentive to default when the amount of liabilities exceeds the value of the collateral, as given in the models of default by Bajari et al. (2008), Foote et al. (2008) and Bhutta et al. (2011). The default option in a full recourse economy is less explored, though the model of Avanzini et al. (2015) shows that in full recourse economies negative equity exhibits the opposite effect on default as households have to pay back the total amount of the loan regardless of the value of the collateral.

The current empirical literature covering European countries focuses on the ability to pay theory. In this case default or arrears on debt is not an intentional choice by a household but the harsh consequence of negative shocks. When households are faced with a negative income shock, the share of debt repayment from their income determines their vulnerability to the shocks. The studies dealing with the financial vulnerability of households use the debt service ratio as the main indicator of financial distress as it denotes households' cash-flow position; see Ampudia et al. (2016) for a recent overview. Equally, differences in the repayment behaviour for housing loans and consumer credit have been detected by Beckmann et al. (2013).

The probability of arrears may be reduced by insurance. There are different ways for households to insure themselves against negative shocks. First, households may use selfinsurance by accumulating buffer-stocks which can be used when negative shocks are faced. Elul et al. (2010) is one of the few studies which investigate the role of illiquidity in mortgage defaults. They use high credit-card use as a proxy for illiquidity or a lack of funds. They find that the illiquidity of households is an important determinant of default on top of negative equity.

Second, households may use networking or help from relatives to cope with financial problems. Lusardi et al. (2011) report that reliance on family and friends is frequently encountered when people deal with emergencies in the USA, in Canada and in European countries.

To summarise, the literature finds that the potential triggers of default or arrears on debt $(D A)$ are income $(Y)$, the debt servicing burden $(D S R)$, and the outstanding amount of a housing loan $\left(D^{H}\right)$ and a consumer loan $\left(D^{C}\right.$ ), while the difficulties can be alleviated by help from family and friends (HELP) or liquid financial assets (FA):

$$
\begin{equation*}
P\left(D A_{i}=1\right)=F\left(Y_{i}, D S R_{i}, D_{i}^{H}, D_{i}^{C}, H E L P_{i}, F A_{i}\right) \tag{1}
\end{equation*}
$$

where

$$
\frac{\partial P\left(D A_{i}\right)}{\partial D S R_{i}}>0, \frac{\partial P\left(D A_{i}\right)}{\partial Y_{i}}<0, \frac{\partial P\left(D A_{i}\right)}{\partial D_{i}^{H}}>0, \frac{\partial P\left(D A_{i}\right)}{\partial D_{i}^{C}}>0, \frac{\partial P\left(D A_{i}\right)}{\partial H E L P_{i}}<0, \frac{\partial P\left(D A_{i}\right)}{\partial F A_{i}}<0
$$

The specification of the empirical model depends on several issues. First, unobserved individual-specific characteristics may be correlated with the covariates. As individualspecific unobserved characteristics are assumed to be time-invariant, using the individualspecific fixed effects model addresses the issue. Second, there is a selection issue as individuals can fall into arrears on debt only when they have a loan. We do not observe debt repayment problems for individuals who do not have a loan, implying that we can only investigate the sample with debt. The selection to debt ownership may be induced by preferences or other unobserved characteristics and credit conditions, as discussed by Kukk (2017). Time invariant individual-specific preferences are dealt with by fixed effects. However, credit conditions change substantially over a business cycle and therefore the selection to borrowers also varies (Sutt et al., 2011). The time-varying selection issue can be addressed by the inclusion of a correction factor in the model as suggested by Heckman (1979) and developed further by Semykina and Wooldridge (2010) among others.

Third, the standard approach for the binary dependant variable is to estimate a non-linear probability model. The fixed effects logit model can be estimated only for a sub-sample in which the dependant variable varies, meaning that only individuals who fall into arrears will be investigated, while indebted individuals who do not experience debt repayment problems are excluded from the model. Moreover, it is not possible to calculate the marginal effects of the variables as the individual-specific effects are not known; the conventional approach of differencing out the individual effects cannot be used for the non-linear binary models, as the estimators for the individual effects and covariates are not independent of each other. The interpretation of the odds ratio is not as straightforward as interpreting the marginal effects would be.

Given the limitations of the fixed effects logit model we follow the suggestion by Angrist and Pischke (2014). They argue that the estimated coefficients in the linear probability model are very close approximations of the marginal effects from the nonlinear model. When the linear probability model is used we can include the full sample of indebted individuals in the model and control for both the time invariant and time varying unobserved heterogeneity.

We estimate a dynamic model so we can take the persistence of the problems into account. The dynamic model estimated by fixed effects suffers from the Nickell bias, but the timeseries dimension of the model is 25 observations, suggesting the bias is relatively small. Moreover, the persistence of the arrears is expected to be rather low as the sample information shows that three quarters of the problems last only one quarter. Judson and Owen (1999) show that the bias is marginal for the autoregressive coefficients and non-existent for the other explanatory variables when the persistence is less than 0.2 . A similar approach has been used by Kukk (2016) for exploring the quarterly dynamics of consumption after individuals face arrears.

The following linear probability model is estimated where the dependant variable is a binary variable that is 1 when an individual faces arrears at the end of the quarter and zero otherwise:

$$
\begin{align*}
D A_{t t}=u_{i}+ & \rho D A_{t-1}+\beta_{1} \log y_{i t}+\beta_{2} \log y_{i t}^{\text {other }}+ \\
& +\gamma_{1} D S R_{t-1}+\gamma_{2} D^{H} t o I_{i t-1}+\gamma_{3} D^{C} t o I_{i t-1}+\gamma_{4} F A t o I_{t-1}+\delta \overline{I M R_{t}}+\tau_{t}+\varepsilon_{i t} \tag{2}
\end{align*}
$$

where $D A_{\mathrm{it}-1}$ denotes the lagged arrears of an individual, $\log y_{\mathrm{it}}$ represents the $\log$ income in the current period and $\log y_{\mathrm{it}}{ }^{\text {other }}$ is the income from other sources. The latter variable captures additional resources from the network. Other debt-related variables which are expected to affect the probability of arrears on debt are the lagged yearly debt service ratio ( $D S R_{\mathrm{it}-1}$ ), the lagged ratio of the balance of a housing loan to yearly income $\left(D^{H} t o I_{\mathrm{it}-1}\right)$ and the lagged ratio of the balance of a consumer loan to yearly income $\left(D^{C} t o I_{\mathrm{it}-1}\right) . F A t o I_{\mathrm{it}-1}$ denotes the lagged ratio of the balance of liquid financial assets to yearly income. All balance sheet variables are lagged by one period and relate to debt or financial assets at the end of the previous quarter. The inclusion of the time dummy $\tau$ controls for aggregate shocks such as changes in credit conditions that affect all individuals similarly.

The IMR is the inverse Mills ratio which controls for the time-varying selection, like in the approach introduced by Wooldridge (1995) and improved further for panel data by Semykina and Wooldridge (2010). The probability of debt ownership is estimated for the full sample, including individuals who do not own any liabilities. The probit model is estimated and the correction factor or the inverse Mills ratio is calculated for each quarter separately. The IMR or the correction factor is included in Equation (2).

## 3. Dataset and descriptive statistics

Estonia is a small euro area country that experienced rapid growth in household debt from the beginning of the 2000s. The aggregate debt-to-income ratio of the household sector grew from the very low level of 15 per cent in 2000 to 88 per cent in 2007, very close to the euro area average of 92 per cent. The rise in indebtedness was induced by several factors, the main ones being financial innovation and capital inflows on the supply side, and increased income, higher income expectations, and the need to improve living conditions on the demand side (Meriküll and Rõõm, 2016). The boom was followed by a bust in 2009 with a sharp decline in income. Average real gross wages fell by 5 per cent in 2009 and the unemployment rate rose
from 5 per cent in mid-2008 to 15 per cent at the end of $2009 .{ }^{1}$ The income decline was accompanied by deleveraging.

Despite the credit boom and the subsequent income decline, households have managed their finances well during the period of turmoil. The European Survey on Income and Living Conditions (EU-SILC) reveals that the share of households that reported being in arrears on mortgage or rent payments peaked in 2010 at 2.7 per cent in Estonia, which is substantially below the EU average of 3.9 per cent. The share of households in arrears on hire purchase instalments or other loan payments reached 4.7 per cent in 2010, which is somewhat above the EU average of 3.2 per cent (Kukk and Staehr, 2013). Although the developments in the credit and labour markets have been profound in Estonia, the implications for the vulnerability of households have been of the same magnitude as in other European countries, suggesting that the reasons behind the financial difficulties are not related to the high debt accumulation but to overall economic conditions. The use of micro data would give valuable insights into the triggers of financial vulnerability in any European country.

The paper uses an anonymised dataset from a financial institution that contains quarterly financial information on individuals from 2004:Q4 to 2011:Q4. The dataset covers 108,000 individuals, which is approximately $12 \%$ of the population aged 20-70. The coverage of the financial sector in Estonia is among the highest in Europe, as 99 per cent of households own a bank account and 37 per cent have an outstanding debt, which is mainly taken from a financial institution (Meriküll and Rõõm, 2016). As the banking sector is highly concentrated in Estonia and bank customers tend to have all their finances in one financial institution (IMF, 2009; OECD, 2011), the data from one financial institution provide a comprehensive picture of the financial situation of a given individual. The financial institution is identified as the main financial service provider for the individuals in the dataset. This restriction implies that the dataset contains all or most of the financial products and transactions of these individuals. Outliers in the balance sheet components and transactions have been excluded.

The most important feature of the dataset for this study is that it contains information about arrears on debt. The financial institution automatically deducts debt servicing payments from the sight account of an individual and if there are not sufficient funds on the sight account to debit, a flag is created. A flag or a dummy denotes arrears on debt at the end of the quarter. There are 11083 incidences of arrears and on average the arrears last two quarters, though 76 per cent of the arrears are short-term delays in repayment as the arrears last no more than one quarter.

Figure 1 shows the development of arrears among indebted individuals and among indebted individuals who have experienced arrears in any of the quarters in 2004-2011. The prevalence of arrears showed a sharp rise in 2008, as the share of individuals with arrears rose from 1.1 per cent of indebted individuals in 2007:Q1 to 2.7 per cent in 2009:Q3 (left-hand graph). In terms of the individuals who fell into arrears during the period (right-hand graph), this sub-sample seems to be a heterogeneous group which experienced arrears at different periods. At the peak, 21 per cent of the sub-sample faced arrears in the same quarter, while the rest experienced arrears in some other quarters. For convenience, we call the sub-sample potentially distressed individuals.

[^1]The share of arrears on debt



Figure 1: The dynamics of the share of arrears on debt from 2004:Q4 to 2011:Q4 in the dataset

The dynamics of arrears in the dataset are consistent with the data on arrears for mortgages and rent from EU-SILC, which are the only data available on arrears in Estonia. According to EU-SILC the presence of arrears was lowest in 2006 and highest in 2010 and the share of arrears grew within that time by a factor of 2.5 .

The dataset includes information about the quarterly inflows to the sight account for each individual. The inflows do not contain transactions between the accounts of the individual, meaning that inflows from personal saving accounts are excluded. Furthermore, it is possible to distinguish between inflows to the sight accounts of an individual from legal entities and those from other sources. The first component contains payments of salaries, social benefits, dividends and self-employment income paid by companies or other legal institutions. This income component is considered to be a proxy for the income of the individual. The second component includes transactions between private individuals or cash deposits on the sight account. The inflow from other sources can be interpreted as contributions from family members, relatives or other individuals. This measure can be used as a proxy for networking.

The nominal variables of the proxies for income are deflated by the HICP consumer price index and real variables are expressed in 2005 prices. Figure 2 shows the quarterly dynamics of the median values of the two income components in the sample of individuals with debt (solid line) and in the sample of individuals experiencing arrears (dashed line). Seasonally fluctuating income from legal entities shows a rise in 2004-2008 and a drop in 2009, which is consistent with aggregate data on household income. The median income in the distressed sample is slightly lower but the income dynamics are similar for the indebted sample and for the distressed sample. The share of the income from other sources is approximately $15-16$ per cent of total income. The right hand graph in Figure 2 shows that the median value of income from other sources increases over the sample period, and it increases slightly more for the distressed sample in 2007-2009. The differences may be related to financial distress.


Figure 2: The dynamics of median quarterly income from 2004:Q4 to 2011:Q4 in the dataset

The dataset contains debt-related information such as quarterly debt servicing payments, the balance of consumer loans and the balance of housing loans. The average balance in the dataset is compared to the average loan amount per contract on the total market, as these are the only statistics which are publicly available. ${ }^{2}$ The comparison for housing loans is given in Figure A. 1 in the Appendix together with the number of indebted individuals and the number of contracts. The same is provided for consumer loans, showing that the dynamics in the dataset and in the market are similar.

As the burden of a particular debt volume for an individual depends on their ability to manage their debt, relative indebtedness is a more informative variable for indebtedness than the absolute debt volume is. Therefore the debt volumes are divided by yearly income from legal entities to calculate the debt to income ratios for housing loans and consumer loans. The dynamics of the median values of the two variables are provided in Figure 3. The values are higher in the distressed sample than in the indebted sample but the dynamics are quite similar in both samples.

The housing loan to income ratio shows some fluctuation over the sample period. The ratio increased in 2005-2006, which was mainly induced by the rise in loan volumes. The housing loan-to-income ratio declined in 2007-2008, when the loan volumes grew at a lower rate than income. In 2009 the ratio started to rise again as income dropped sharply. In 2011 there was a decrease in the ratio as the loan volumes declined. The upshot is that the increase in the housing loan-to-income ratio is accompanied by a rise in arrears on debt as the penetration of arrears is higher after 2009, suggesting that the housing loan-to-income ratio may be a potential trigger for arrears.

[^2]

Figure 3: The dynamics of median quarterly housing and consumer loan to income ratio from 2005:Q3 to 2011:Q4 in the dataset, conditional on debt ownership

The consumer debt to income ratio in the right hand graph in Figure 3 reveals the median consumer debt-to-income ratio in the indebted sample to be decreasing slightly. In the distressed sample the ratio increased until the end of 2007 and declined after that. Hence the rise in the presence of arrears coincides with a decline in the median consumer loan-to-income ratio in this group.

Furthermore, the dataset contains information about the debt service ratio and the development of the ratio is presented in Figure 4. The yearly payments are divided by yearly income from legal institutions. The variable covers both principal and interest payments for all types of loan, measuring the overall debt servicing burden of the individual.

The left-hand graph in Figure 4 shows that the median value of the debt service ratio increased when the economy was growing in 2007 and continued to rise in the recession until the end of 2009. The rise is sharper among individuals who experienced arrears. The ratio grew at the same time that the share of arrears increased. In 2010 the debt service ratio started to decline, apparently because of the drop in loan volumes.

Finally, the liquid assets to yearly income ratio is computed and the ratio is used to assess the role of liquidity in arrears. Liquid financial assets contain the balance of sight and saving accounts, stocks, bonds and investment funds. The dynamics of the ratio are illustrated in Figure 4, showing seasonal fluctuations for the median value in the indebted sample. As the ratio is between $0.02-0.03$, the balance of the liquid assets covered less than half of a month's income. The median liquid asset ratio is even lower among individuals who experienced arrears, which is not surprising as arrears can only arise when there are no funds on the sight account. The full list of the variables used in the database and the main statistics are given in Table A. 1 in the Appendix.


Figure 4: The dynamics of the median debt service burden, conditional on debt ownership, and the liquid assets-to-income ratio in the dataset from 2005:Q3 to 2011:Q4

## 4. The estimations

### 4.1. Estimations on the full sample

Equation (2) is estimated for the sub-sample of individuals whose balance of liabilities is positive: there are approximately 65 thousand indebted individuals in the sample and 7.3 thousand of them experience arrears at least once over the sample period. The estimation results of different probability models are provided in Table 1 . We see that the linear probability models for pooled and random effects in Columns (2) and (3) provide identical results, while the estimated coefficients of the fixed effects linear probability model in Column (1) are somewhat different. The Hausman test shows that the estimated coefficients in the random effects model are not consistent and therefore the fixed effects model is preferred.

We focus on the estimations in Column (1) in Table 1. The estimations show low persistence of arrears on debt, which is not surprising as three quarters of the arrears in the sample last no more than one quarter. The estimated coefficient of income is negative, as 1 per cent lower income is associated with a 0.016 percentage point higher probability of arrears. We see from Figure 2 in Section 3 that the median income in 2009 declined by 6.7 per cent from 2008, which is associated with a 0.11 percentage point higher share of arrears, ceteris paribus. At the same time the share of the sample in arrears increased by 0.5 percentage point, from 1.7 per cent to 2.2 per cent, suggesting that income decline made an important contribution to the increase in arrears. Mocetti and Viviano (2014) estimate conditional logit with fixed effects and find yearly income change to be negatively correlated with bad or substandard loans or past due, although the impact is negligible. The current quarterly estimations provide clear evidence for the role of an income decline in debt repayment problems.

Table 1: Estimation results for arrears on debt. Comparison of different model specifications

|  | (1) <br> Linear FE | $\begin{gathered} \text { (2) } \\ \text { Linear RE } \end{gathered}$ | (3) Pooled |
| :---: | :---: | :---: | :---: |
| arrear $_{\text {it- }}$ | $\begin{aligned} & \hline 0.1849 * * * \\ & (0.0050) \end{aligned}$ | $\begin{aligned} & \hline 0.3983 * * * \\ & (0.0059) \end{aligned}$ | $\begin{aligned} & \hline 0.4027 * * * \\ & (0.0037) \end{aligned}$ |
| $\log y_{i t}$ | $\begin{aligned} & -0.0156^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0120^{* * *} \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & -0.0119^{* * *} \\ & (0.0002) \end{aligned}$ |
| $\log y_{i t}^{\text {other }}$ | $\begin{aligned} & -0.0011 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0010 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0010^{* * *} \\ & (0.0000) \end{aligned}$ |
| $D S R_{i-1}$ | $\begin{aligned} & 0.0065 * * * \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & 0.0025 * * * \\ & (0.0007) \end{aligned}$ | $\begin{aligned} & 0.0024^{* * *} \\ & (0.0005) \end{aligned}$ |
| $D^{H} t o I_{i t-1}$ | $\begin{aligned} & 0.0006 * * * \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & 0.0013 * * * \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & 0.0013 * * * \\ & (0.0001) \end{aligned}$ |
| $D^{C}{ }_{\text {toI }}{ }_{i t-1}$ | $\begin{aligned} & 0.0075^{* * *} \\ & (0.0015) \end{aligned}$ | $\begin{aligned} & 0.0137 * * * \\ & (0.0012) \end{aligned}$ | $\begin{aligned} & 0.0137 * * * \\ & (0.0009) \end{aligned}$ |
| FAtoI ${ }_{\text {in-1 }}$ | $\begin{aligned} & -0.0001 \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & 0.0005^{*} \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0005^{* *} \\ & (0.0002) \end{aligned}$ |
| $I M R_{i t}$ | $\begin{aligned} & -0.0081^{* * *} \\ & (0.0007) \end{aligned}$ | $\begin{aligned} & -0.0164 * * * \\ & (0.0005) \end{aligned}$ | $\begin{aligned} & -0.0164 * * * \\ & (0.0004) \end{aligned}$ |
| No. of obs. | 1031625 | 1031625 | 1031625 |
| No. of groups | 65310 | 65310 | 65310 |
| $\mathrm{R}^{2}$ | 0.042 | 0.039 |  |
| $\chi^{2}$ <br> Hausman test $\chi^{2}$ (p-value for RE) |  | $\begin{aligned} & 274072 \\ & (0.000) \end{aligned}$ |  |

Notes: FE estimation of eq. (2). Time dummies are included in the estimations but not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ***, ** and * indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively. The Hausman test is for the hypothesis that the estimated coefficients in the RE model are consistent.

The estimated coefficient for the income from sources other than legal entities is -0.001 , implying that a rise of 10 per cent in this income source is associated with a 0.01 percentage point lower probability of arrears. As seen in Figure 2, the median values are smaller for the income from other sources than for the income from legal entities, but this income doubled in 2006-2008, suggesting that during this period transfers from other individuals could have had a significant role in reducing the risk of arrears, as an average increase of 100 per cent in this income source would be related to a 0.1 percentage point lower share of individuals in arrears.

All debt related variables are positively associated with the probability of default. The estimated coefficient for the lagged debt service ratio is 0.0065 . To understand the magnitude of the estimated marginal effect, we look at the change in the median ratio for the indebted sample. The ratio increased by 6 percentage points ( 0.06 points) in 2006-2009, which would be associated with a rise in the share of arrears of 0.04 percentage point.

The estimated coefficient for the housing loan-to-yearly income ratio is 0.0006 and for the consumer loan it is 0.0075 . A rise of 0.3 points in the median housing loan-to-income ratio was observed in 2009-2010 and it would be related to a 0.02 percentage point higher share of arrears. The median consumer loan-to-income ratio grew by 0.04 point in 2006-2007, and a rise in the ratio of this magnitude would raise the share of arrears by 0.03 percentage point. The results indicate that on top of the debt service ratio, the impact from the balance of housing and consumer loans on arrears is present, though it is relatively small compared to the impact from income decline.

The coefficient of the lagged liquid financial assets-to-yearly income ratio is not statistically significant, suggesting that the accumulation of financial assets does not reduce the probability of financial difficulties. The estimated IMR is negative and statistically significant, implying that the characteristics which are positively related to debt ownership lower the probability of arrears.

As income is the denominator in the debt-related variables, the sensitivity of the estimated coefficient of income is tested by including other variables one-by-one in Equation (2). As can be seen in Table A. 2 in the Appendix, the coefficient of income is very stable to different sets of variables. The coefficient for the debt service ratio also catches the aggregate shocks, as the coefficient is larger when time dummies are not included. It is noteworthy that the estimated coefficients of the explanatory variables are not very similar to the baseline model when the selection to debt ownership is not controlled for.

Additional estimations have been done in different sub-samples to assess the robustness of the results. Table A. 3 in the Appendix provides the estimations by gender and by age group. The estimated coefficients for males and females are very similar, indicating that the triggers are the same regardless of gender. Similarly, the estimated coefficients are not statistically different across the age groups. The upshot of the different estimations is that the baseline estimations in Column (1) in Table 1 are very robust to different model specifications.

The main finding of the estimations is that the income decline is the main trigger for falling into arrears while the debt service burden is also an important trigger, confirming the "ability to pay" theory. Comparable results have been obtained in the stress tests by Meriküll and Rõõm (2017). They use the Estonian Household Finance and Consumption Survey from 2013 and find that the probability of default increases both when the unemployment rate rises, cutting income, and when the interest rate rises, increasing the debt service ratio.

### 4.2. Estimations by income quintiles

The probability of default is expected to be heterogeneous across income groups, particularly when the ability to pay is the main trigger for arrears. There are several papers that emphasise the importance of income distribution and heterogeneity in the responses to shocks. Mian et al. (2013) show that poor and more indebted households are more vulnerable to wealth shocks. Kumhof et al. (2015) use a theoretical model to explain how unequal distribution of income increases financial fragility.

Figure 5 presents the share of individuals with arrears, conditional on debt ownership, in each income quintile. Individuals in the full sample are split into quintiles based on the
average income over the period 2004:Q4-2011:Q4. The share of individuals in arrears is highest in the lowest income group, and in 2006:Q4 the share was 1.8 per cent while in the highest income group the share was one third of this at 0.6 per cent. The lowest income group also experienced the largest rise in arrears as the share increased to 4 per cent in 2009:Q3.


Figure 5: The share of individuals with arrears on debt by income quantile from 2005:Q3 to 2011:Q4, conditional on debt ownership

Equation (2) is extended so that the marginal effects of the explanatory variables are allowed to vary across five income groups:

$$
\begin{align*}
D A_{i t}=u_{i}+ & \sum_{q=1}^{5} \rho_{q} d_{q} D A_{i t-1}+\sum_{q=1}^{5} \beta_{1 q} d_{q} \log y_{i t}+\sum_{q=1}^{5} \beta_{2 q} d_{q} \log y_{i t}^{\text {other }}+ \\
& +\sum_{q=1}^{5} \gamma_{1 q} d_{q} D S R_{i t-1}+\sum_{q=1}^{5} \gamma_{2 q} d_{q} D^{H} T I_{i-1}+\sum_{q=1}^{5} \gamma_{3 q} d_{q} D^{C} T I_{i-1}+  \tag{3}\\
& +\sum_{q=1}^{5} \gamma_{4 q} d_{q} F A_{i t-1}+\sum_{q=1}^{5} \delta_{q} d_{q} \overline{I M R_{t t}}+\tau_{t}+\varepsilon_{i t}
\end{align*}
$$

The dummy $d_{q}$ stands for the income quintile q while the coefficient $\rho_{q}$ denotes the persistence in the q -th income quintile and $\beta_{l q}$ denotes the relationship between income and the probability of arrears in the q -th income quintile. Table 2 provides the estimations.

Table 2: Estimation results for arrears on debt by income quintiles. Linear fixed effects estimations

|  | (1) <br> Quintile 1 | (2) <br> Quintile 2 | (3) <br> Quintile 3 | (4) <br> Quintile 4 | (5) <br> Quintile 5 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| arrear $_{\text {it- }}$ | 0.1657*** | 0.1932*** | 0.1919*** | 0.2034*** | 0.1626*** |
|  | (0.0126) | (0.0109) | (0.0110) | (0.0109) | (0.0108) |
| $\log y_{i t}$ | -0.0219*** | $-0.0196 * * *$ | $-0.0164^{* * *}$ | -0.0150 *** | $-0.0120 * * *$ |
|  | (0.0018) | (0.0012) | (0.0010) | (0.0009) | (0.0008) |
| $\log y_{i t}^{\text {other }}$ | -0.0014*** | $-0.0012^{* * *}$ | $-0.0012^{* * *}$ | $-0.0011^{* * *}$ | $-0.0008 * * *$ |
|  | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $D S R_{u-1}$ | 0.0180*** | 0.0072*** | 0.0060*** | 0.0064*** | 0.0020 |
|  | (0.0038) | (0.0022) | (0.0019) | (0.0016) | (0.0016) |
| $D^{H}$ tol $_{i t-1}$ | -0.0001 | 0.0019** | 0.0011** | $0.0008^{* *}$ | 0.0004 |
|  | (0.0015) | (0.0008) | (0.0005) | (0.0004) | (0.0003) |
| $D^{c}{ }_{\text {tol }}{ }_{i t-1}$ | -0.0017 | 0.0073** | 0.0087*** | 0.0047 | 0.0138*** |
|  | (0.0052) | (0.0033) | (0.0028) | (0.0031) | (0.0038) |
| FAtoI ${ }_{\text {ki-1 }}$ | -0.0036*** | 0.0003 | -0.0009 | -0.0004 | 0.0003 |
|  | (0.0011) | (0.0006) | (0.0007) | (0.0005) | (0.0003) |
| IMR | 0.0005 | $-0.0087^{* * *}$ | $-0.0082^{* * *}$ | $-0.0100^{* * *}$ | $-0.0121^{* * *}$ |
|  | (0.0027) | (0.0019) | (0.0018) | (0.0014) | (0.0013) |
| No. of obs. |  |  | 1031625 |  |  |
| No. of groups |  |  | 65310 |  |  |
| $\mathrm{R}^{2}$ |  |  | 0.042 |  |  |

Notes: FE estimation of eq. (3). Time dummies are included in the estimations but not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ***, ** and * indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

The liquid asset-to-income ratio matters for the probability of arrears in the lowest income group and individuals in lower income groups are more sensitive to income changes than individuals in higher income groups are. Similarly, a higher debt service ratio is associated most strongly with arrears in the lowest income group, while arrears in the highest income group are not related to the debt service ratio, ceteris paribus. The estimated coefficient for the consumer loan-to-income ratio is higher for the highest income group, suggesting that arrears for this group are related to the balance of consumer loans rather than to the debt service ratio, while the housing loan is not associated with arrears in this income group. The results indicate that individuals in the highest income group are more willing to fall into arrears on their consumer loans regardless of their ability to pay, implying strategic behaviour. The ability to pay theory applies more clearly to the lowest income group.

### 4.3. Estimations by years

Figure 1 shows that the presence of arrears increased markedly in 2009 when the recession hit households' wages and employment. In order to investigate whether the income change or the balance sheet variables exhibit different effects on arrears in different time periods, the estimated coefficients are allowed to vary in different years:

$$
\begin{align*}
D A_{i t}=u_{i}+ & \sum_{p=1}^{6} \rho_{p} d_{p} D A_{i t-1}+\sum_{p=1}^{6} \beta_{1 p} d_{p} \log y_{i t}+\sum_{p=1}^{6} \beta_{2 p} d_{p} \log y_{i t}^{\text {other }}+ \\
& +\sum_{p=1}^{6} \gamma_{1 p} d_{p} D S R_{i t-1}+\sum_{p=1}^{6} \gamma_{2 p} d_{p} D^{H} T I_{i t-1}+\sum_{p=1}^{6} \gamma_{3 p} d_{p} D^{C} T I_{i t-1}+  \tag{4}\\
& +\sum_{p=1}^{6} \gamma_{4 p} d_{p} F A_{i t-1}+\sum_{p=1}^{6} \delta_{p} d_{p} \overline{I M R_{i t}}+\tau_{t}+\varepsilon_{i t}
\end{align*}
$$

The dummy $d_{p}$ stands for the time periods $p$, which are the years from 2006 to 2011. The estimations are given in Table 3.

The persistence of arrears was lowest in 2007 but increased after that. The marginal effect of income from legal institutions is stable over the years, but income from other sources exhibits a stronger relationship with the probability of arrears after 2009. By that time the median income from other sources had doubled from what it was in the median income in 2006, as also seen in Figure 2 in Section 3.

The debt service ratio exhibits a somewhat stronger impact on the probability of arrears in 2008-2009, indicating that during the recession the probability of arrears was affected more by the debt service ratio. The housing loan-to-income ratio is not associated with the probability of arrears when the economy was growing, while a modest relationship is seen after 2008, although the economic magnitude is very small.

There are substantial differences in the estimated coefficients for the consumer loan. The consumer loan is negatively associated with debt repayment problems in 2006 and a positive relationship appears in 2008 and is strongest in 2010. The estimated coefficient is 0.0367 in 2010, while for the full sample period it is 0.0075 (Table 1 Column (1) in Sub-section 4.1). Apparently the role of consumer loans in arrears has increased since the recession and further estimations are implemented in the following sub-sections to provide additional insights into the relationship between arrears and different types of loans.

The ratio of liquid assets to income is not related to the probability of arrears in 2005-2008. In 2009-2010 the negative coefficient is statistically significant but as the average ratio in the sample is small, the economic effect on arrears is negligible.

Table 3: Estimation results for arrears on debt in different time periods. Linear fixed effects estimations

|  | $\begin{gathered} (1) \\ 2006 \end{gathered}$ | $\begin{gathered} \hline(2) \\ 2007 \end{gathered}$ | $\begin{gathered} (3) \\ 2008 \end{gathered}$ | $\begin{gathered} (4) \\ 2009 \end{gathered}$ | $\begin{gathered} \hline(5) \\ 2010 \end{gathered}$ | $\begin{gathered} (6) \\ 2011 \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| arrear $_{\text {it-1 }}$ | $\begin{aligned} & \hline 0.1089 * * * \\ & (0.0130) \end{aligned}$ | $\begin{aligned} & 0.0731 * * * \\ & (0.0112) \end{aligned}$ | $\begin{aligned} & 0.1419 * * * \\ & (0.0095) \end{aligned}$ | $\begin{aligned} & \hline 0.1819 * * * \\ & (0.0089) \end{aligned}$ | $\begin{aligned} & 0.2191 * * * \\ & (0.0086) \end{aligned}$ | $\begin{aligned} & 0.2660^{* * *} \\ & (0.0095) \end{aligned}$ |
| $\log y_{i t}$ | $\begin{aligned} & -0.0159 * * * \\ & (0.0005) \end{aligned}$ | $\begin{aligned} & -0.0154^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0154^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0151^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0151^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0151^{* * *} \\ & (0.0004) \end{aligned}$ |
| $\log y_{i t}^{\text {other }}$ | $\begin{aligned} & -0.0006^{* * *} \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0008^{* * *} \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0009^{* * *} \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0012^{* * *} \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0014 * * * \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0015^{* * *} \\ & (0.0001) \end{aligned}$ |
| $D S R_{u-1}$ | $\begin{aligned} & 0.0046^{* *} \\ & (0.0020) \end{aligned}$ | $\begin{aligned} & 0.0028^{*} \\ & (0.0017) \end{aligned}$ | $\begin{aligned} & 0.0056^{* * *} \\ & (0.0015) \end{aligned}$ | $\begin{aligned} & 0.0058^{* * *} \\ & (0.0016) \end{aligned}$ | $\begin{aligned} & 0.0047 * * * \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & 0.0039 * * * \\ & (0.0015) \end{aligned}$ |
| $D^{H} t o I_{i t-1}$ | $\begin{aligned} & -0.0002 \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0003 \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & 0.0010^{* * *} \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0010^{* * *} \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0008 * * * \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0010^{* * *} \\ & (0.0003) \end{aligned}$ |
| $D^{c}$ toI ${ }_{i t-1}$ | $\begin{aligned} & -0.0073 * * * \\ & (0.0022) \end{aligned}$ | $\begin{aligned} & -0.0035^{*} \\ & (0.0021) \end{aligned}$ | $\begin{aligned} & 0.0044^{*} \\ & (0.0023) \end{aligned}$ | $\begin{aligned} & 0.0249 * * * \\ & (0.0030) \end{aligned}$ | $\begin{aligned} & 0.0367 * * * \\ & (0.0035) \end{aligned}$ | $\begin{aligned} & 0.0331^{* * *} \\ & (0.0038) \end{aligned}$ |
| FAtoI | $\begin{aligned} & 0.0004 \\ & (0.0003) \end{aligned}$ | $\begin{aligned} & 0.0001 \\ & (0.0001) \end{aligned}$ | $\begin{aligned} & -0.0008 \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & -0.0016^{* * *} \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & -0.0020^{* *} \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & -0.0002 \\ & (0.0003) \end{aligned}$ |
| $I M R_{i t}$ | $\begin{aligned} & -0.0056^{* * *} \\ & (0.0011) \end{aligned}$ | $\begin{aligned} & -0.0078 * * * \\ & (0.0010) \end{aligned}$ | $\begin{aligned} & -0.0065^{* * *} \\ & (0.0010) \end{aligned}$ | $\begin{aligned} & -0.0082^{* * *} \\ & (0.0011) \end{aligned}$ | $\begin{aligned} & -0.0087 * * * \\ & (0.0012) \end{aligned}$ | $\begin{aligned} & -0.0084^{* * *} \\ & (0.0011) \end{aligned}$ |
| No. of obs. | 1031625 |  |  |  |  |  |
| No. of groups | 65310 |  |  |  |  |  |
| $\mathrm{R}^{2}$ | 0.047 |  |  |  |  |  |

Notes: FE estimation of eq. (4). Lags 2-4 of the dependent variable and income variables are included in the estimations as well as all time dummies but not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ${ }^{* * *}$, ** and * indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

### 4.4. The probability of arrears for new loans

The ability to identify the timing of when a new loan is taken allows investigation of whether individuals tend to fall into arrears shortly after or some time after taking the loan. Information about a new or an additional loan is derived from the balance of liabilities. It is assumed that a new housing loan has been granted when the balance of the housing loan is positive at the end of the quarter but was zero in the previous quarter. An additional housing loan is granted when the balance of the housing loan at the end of the quarter is higher than it was at the end of the previous quarter. Similarly, a new or additional consumer loan is identified from comparison of the balance of consumer loans at the ends of the sequence of quarters.

Dummies denoting a new or additional housing loan and a consumer loan are added to the model given in Equation (2). Both the contemporaneous and four lagged dummies are included. The contemporaneous dummy estimates the linkage between arrears on debt and a new or additional loan in the same quarter that the loan is granted. Lagged dummies show
how a new or additional loan is associated with the probability of arrears arising in the quarters after the loan has been granted. All the other variables in Equation (2) are included in the regression. The estimated coefficients of the dummies for a new or additional loan are given in Table 4.

Table 4: Estimation results for arrears on debt, dummies for a new or additional housing loan and for a consumer loan

|  | (1) <br> New housing loan | (2) Additional housing loan | (3) <br> New consumer loan | (4) Additional consumer loan |
| :---: | :---: | :---: | :---: | :---: |
| $t$ | $\begin{aligned} & \hline-0.0083 * * * \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & -0.0102 * * * \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & \hline 0.0011^{*} \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & \hline 0.0046 * * * \\ & (0.0004) \end{aligned}$ |
| $t-1$ | $\begin{aligned} & -0.0049 * * * \\ & (0.0013) \end{aligned}$ | $\begin{aligned} & -0.0028 * * \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & -0.0032 * * * \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & -0.0009 * * * \\ & (0.0004) \end{aligned}$ |
| $t-2$ | $\begin{aligned} & -0.0025^{*} \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & -0.0030^{* *} \\ & (0.0013) \end{aligned}$ | $\begin{aligned} & -0.0036 * * * \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & -0.0002 \\ & (0.0004) \end{aligned}$ |
| $t-3$ | $\begin{aligned} & -0.0015 \\ & (0.0015) \end{aligned}$ | $\begin{aligned} & -0.0007 \\ & (0.0013) \end{aligned}$ | $\begin{aligned} & -0.0023 * * * \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & -0.0002 \\ & (0.0003) \end{aligned}$ |
| $t-4$ | $\begin{aligned} & -0.0009 \\ & (0.0014) \end{aligned}$ | $\begin{aligned} & -0.0002 \\ & (0.0013) \end{aligned}$ | $\begin{aligned} & -0.0022^{* * *} \\ & (0.0005) \end{aligned}$ | $\begin{aligned} & 0.0004 \\ & (0.0003) \end{aligned}$ |
| No. of obs. | 944984 |  |  |  |
| No. of groups | 63994 |  |  |  |
| $\mathrm{R}^{2}$ | 0.040 |  |  |  |

Notes: FE estimation of eq. (2), to which dummies for new and additional loans have been added. All explanatory variables and time dummies are included in the estimations but the results for these are not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ${ }^{* * *},{ }^{* *}$ and $*$ indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

The estimated coefficients for the contemporaneous dummy and for the dummy of a new housing loan lagged one period are negative and statistically significant, indicating that the probability of arrears is lower in the same quarter when the loan is granted and also in the following quarter. Similarly, the probability of arrears is lower in the same quarter and the two quarters after an additional housing loan has been granted. The estimations show that individuals manage recently granted housing loans fairly well. The stronger negative relationship between arrears and an additional housing loan might be related to credit conditions, as individuals who have experienced debt repayment problems have a restricted ability to borrow additionally. However, the results for an additional consumer loan do not suggest a similar selection issue.

A different picture emerges for consumer loans. The probability of arrears is somewhat higher in the quarter when a new consumer loan is issued but the probability is lower in the
following quarters. Similarly, the probability of arrears is higher in the quarter when an additional consumer loan is granted but it is lower in the following quarter. The balance of consumer loans contains all types of short-term loans, such as overdrafts, credit balances on credit cards and revolving cards. It is not possible to distinguish between different types of consumer loans to investigate further whether the results vary for different types of consumer loan.

It can be hypothesised that individuals in financial difficulties may search for help from short-term loans such as the use of a credit limit. The hypothesis has been explored by regressing a dummy for an additional consumer loan on a set of explanatory variables, and the estimations are given in Table A. 4 in the Appendix. An income decline, a higher debt service ratio and a lower level of liquid financial assets are positively associated with an additional consumer loan, while the opposite relationship is found between income, the debt service ratio, liquid financial assets and an additional housing loan. The results are consistent with the hypothesis that additional consumer loans might be related to financial difficulties. Similarly, Herkenhoff and Ohanian (2012) have found that US households use mortgage payment delinquency as an undocumented line of credit.

### 4.5. Does it matter when a new loan is granted?

We explore further the linkage between arrears and new loans by distinguishing the period when a loan is taken. This can shed more light on the role of credit conditions and house prices, which varied substantially during the sample period. As seen in Figure A. 1 in Appendix A, there was a sharp rise in the volumes and penetration of both housing and consumer loans in 2006-2007. To a large extent the boost in the volumes was induced by the easing of credit conditions from 2005 and pro-active offers of consumer loans by financial institutions (Kukk and Staehr, 2013; Sutt et al., 2011). If the relaxation of the credit conditions is related to the rise in the incidences of arrears, new housing and consumer loans granted in 2006-2007 are expected to exhibit a higher probability of arrears than loans issued in other periods.

Additionally, housing loans issued when house prices were at their peak are expected to exhibit a lower probability of arrears. In Estonia, as in the other European countries, full recourse loans are prevalent (Bardhan et al., 2011). Ghent and Kudlyak (2011) show that full recourse affects default by lowering the sensitivity of borrowers to negative equity.

The dynamics of the real house price index are shown in Figure 6. There was an upsurge in house prices in 2005-2007, when the house price index rose by 90 per cent to peak in 2007:Q2. The rise was followed by a sharp drop of approximately 50 per cent in house prices until they reached a trough in 2009:Q4. Given that it was possible to take a housing loan without any down-payment during the boom, the dynamics in house prices indicate that many housing loans taken in 2006-2007 were underwater after 2008 (OECD, 2009).


Figure 6: The dynamics of the deflated house price index in Estonia 2005:Q1-2011:Q4 Source: Eurostat.

When the economy was growing there were several factors which affected the probability of arrears in opposite directions. To explore whether the housing loans granted in 2006-2007 exhibit a lower or higher probability of arrears, the dummy for a new housing loan is interacted with year dummies, which are added to Equation (2). All the other explanatory variables in Equation (2) are also included. In the current model specification, the role of house prices cannot be disentangled from the role of credit conditions. The estimated coefficients for the interaction term are given in Column (1) in Table 5. In this model specification the reference group contains housing loans granted before 2006.

Table 5 reveals that the probability of arrears is lower for housing loans issued in 2007 than for loans granted in 2006 and earlier. The probability of arrears is even lower for loans granted in 2008-2011. The stronger negative relationship in 2008-2011 is supported by credit conditions being tighter during this period. As credit conditions were more flexible when the economy was growing, potentially leading to a higher probability of arrears, the estimated negative coefficient for new housing loans taken in 2007 is apparently driven by house prices.

Interaction between new consumer loan dummies and year dummies was included in the same model to give help in understanding the role of the change in the credit conditions for consumer loans. The estimated coefficients for the dummies of new consumer loans granted in each year are provided in Column (2) in Table 5. The probability of facing arrears is higher for consumer loans issued in any year after 2007 and is highest for consumer loans taken in 2008, which is the year when the credit conditions were tightened. Consumer loans granted in 2011 show a lower probability of arrears, reflecting tight credit conditions.

The results indicate that the higher probability of arrears in consumer loans is not explicitly driven by the easing of credit conditions in 2006-2007 but by other factors which made individuals take loans in 2007-2009. As already mentioned in Sub-section 4.4, there is some evidence that new consumer loans were taken to alleviate financial difficulties, which were especially severe in 2008-2009 when labour market conditions worsened.

Table 5: Estimation results of the baseline model including dummies for years when a housing or consumer loan was taken

| New housing loan | (1) <br> Linear FE | New consumer loan | (2) <br> Linear FE |
| :---: | :---: | :---: | :---: |
| $n e w D_{2006}^{H}$ | $\begin{aligned} & \hline-0.0045^{* *} \\ & (0.0019) \end{aligned}$ | $n e w D_{2006}^{C}$ | $\begin{aligned} & \hline 0.0012 \\ & (0.0011) \end{aligned}$ |
| $n e w D_{2007}^{H}$ | $\begin{aligned} & -0.0073 * * * \\ & (0.0017) \end{aligned}$ | $n e w D_{2007}^{C}$ | $\begin{aligned} & 0.0027^{* * *} \\ & (0.0010) \end{aligned}$ |
| $n e w D_{2008}^{H}$ | $\begin{aligned} & -0.0130^{* * *} \\ & (0.0037) \end{aligned}$ | $n e w D_{2008}^{C}$ | $\begin{aligned} & 0.0048^{* * *} \\ & (0.0012) \end{aligned}$ |
| $n e w D_{2009}^{H}$ | $\begin{aligned} & -0.0112^{* *} \\ & (0.0054) \end{aligned}$ | $n e w D_{2009}^{C}$ | $\begin{aligned} & 0.0026 * * \\ & (0.0012) \end{aligned}$ |
| $n e w D_{2010}^{H}$ | $\begin{aligned} & -0.0118^{* *} \\ & (0.0047) \end{aligned}$ | $n e w D_{2010}^{C}$ | $\begin{aligned} & -0.0010 \\ & (0.0011) \end{aligned}$ |
| $n e w D_{2011}^{H}$ | $\begin{aligned} & -0.0117 * * \\ & (0.0057) \end{aligned}$ | $n e w D_{2011}^{C}$ | $\begin{aligned} & -0.0029 * * \\ & (0.0011) \end{aligned}$ |
| No. of obs. |  | 1031625 |  |
| No of groups |  | 65310 |  |
| $\mathrm{R}^{2}$ |  | 0.042 |  |

Notes: FE estimation of eq. (2). All explanatory variables and time dummies are included in the estimations but the results for these are not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts $* * *, * *$ and $*$ indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

The results for new housing loans indicate tentatively that the role of the value of the collateral is different for full recourse and non-recourse countries. May and Tudela (2005) do not find any evidence that the amount of housing equity or the presence of negative equity affects the probability of mortgage payment problems among UK households in 1992-2002. Mocetty and Viviano (2014) also include house price indexes on a regional level in their regression, but this variable is not statistically significant in explaining the presence of bad loans. Our estimations reveal that it matters for the probability of arrears which year a new housing loan is issued in, and this result apparently captures among other things the effect of house prices.

## 5. Conclusions

This paper investigates the role of income and indebtedness in triggering arrears on debt in Estonia, a euro area country with full recourse loans. It is hypothesised that the main trigger is income decline, while balance sheet components can also be related to the probability of arrears. As a quarterly panel from 2005:Q4-2011:Q4 is used, the estimated fixed effects model controls for the unobserved heterogeneity and the estimations can be carried out for different sub-samples and business cycle periods.

The estimations reveal that an income decline and the debt service ratio are important triggers for arrears, confirming the "ability to pay" theory. On top of the debt servicing burden, the role of indebtedness arising from consumer loans is noticeable in 2009-2011, while housing loans exhibit a negligible role in the probability of arrears. Estimations for different income quintiles show that the probability of arrears is most sensitive in the lowest income group to an income decline and to the debt servicing burden. The probability of arrears is insensitive to the debt service ratio in the highest income group and in this group the arrears are driven by the balance of consumer loans instead, suggesting strategic behaviour by individuals in the highest income group. The results from different business cycle periods indicate that the effect of the debt service ratio and of liquid assets is stronger during the recession, while the role of consumer loans in inducing arrears increased after the recession.

Further estimations indicate that a new or additional housing loan is associated with a lower probability of arrears. Moreover, the estimations reveal that loans taken when the economy was growing exhibit a lower probability of arrears. Although this period was accompanied both by easier credit conditions and by high house prices, individuals did not tend to fall into arrears.

A different picture emerges for consumer loans, as the probability of arrears is markedly higher in the quarter when a consumer loan is granted, suggesting that consumer loans have been used to alleviate financial difficulties. However, the evolution in the probability of arrears cannot be explained by the change in credit conditions as the loans granted under a strict credit policy in 2008-2011 exhibit a higher probability of arrears than loans granted in 2005-2006, when credit conditions were relaxed.

The results of the paper improve the understanding about the triggers for arrears on debt, indicating that an income decline is an important trigger for arrears while indebtedness also plays some role in falling into arrears. To the best of our knowledge this is one of the first studies to compare explicitly the role of housing loans and consumer loans in arrears and we reveal that the two loan types show diverse patterns in the probability of arrears.

The results of the paper indicate that an important way to address the issue of debt repayment problems is to alleviate negative income shocks and the debt service burden. One of the main measures for alleviating income shocks is self-insurance by accumulation of liquid assets, but the results show that this measure does not to play any role in preventing arrears. Therefore measures which mitigate the debt service burden, such as lowering interest rates or rescheduling loan payments, are more efficient in tackling arrears on debt.

## References

AMPUDIA, M., H. VAN VLOKHOVEN, AND D. L. ŻOCHOWSKI (2016): Financial fragility of euro area households. Journal of Financial Stability, forthcoming [http://dx.doi.org/10.1016/j.jfs.2016.02.003]

ANGRIST, J. D., AND J. S. PISCHKE (2014): Mastering'metrics: the path from cause to effect. Princeton University Press.
AVANZINI, D., J. F. MARTÍNEZ, AND V. PÉREZ (2015): A micro-powered model of mortgage default risk for full recourse economies, with an application to the case of Chile. Irving Fischer Committee on Central Banks Statistics, Workshop in Warsaw in December 2015. Available at https://www.bis.org/ifc/publ/ifcb41v.pdf

BAJARI, P., C. S. CHU, D. NEKIPELOV, AND M. PARK (2013): A dynamic model of subprime mortgage default: estimation and policy implications. National Bureau of Economic Research, Working Paper, No. w18850.

BAJARI, P., C. S. CHU, AND M. PARK (2008): An empirical model of subprime mortgage default from 2000 to 2007. National Bureau of Economic Research, Working Paper, No. w14625.

BARDHAN, A., R. EDELSTEIN, AND C. A. KROLL (2011): A Comparative Context for U.S. Housing Policy: Housing Markets and the Financial Crisis in Europe, Asia, and Beyond. UC Berkeley: Fisher Center for Real Estate and Urban Economics.

BHUTTA, N., J. DOKKO, AND H. SHAN (2011): Consumer Ruthlessness and Mortgage Default During the 2007-2009 Housing Bust. Federal Reserve Board of Governors Working Paper.

BECK, T., K. KIBUUKA, AND E. R. TIONGSON (2010): Mortgage finance in central and eastern Europe--opportunity or burden?. World Bank Policy Research Working Paper Series, No. 5202.

BÖHEIM, R., AND M. P. TAYLOR (2000): My home was my castle: evictions and repossessions in Britain. Journal of Housing Economics, 9(4), pp. 287-319.

CONNOR, G., AND T. FLAVIN (2015): Strategic, unaffordability and dual-trigger default in the Irish mortgage market. Journal of Housing Economics, Vol. 28, pp. 59-75.

DUYGAN-BUMP, B., AND C. GRANT (2009): Household debt repayment behaviour: what role do institutions play?. Economic Policy, Vol. 24(57), pp. 108-140.

ELUL, R., N. S. SOULELES, S. CHOMSISENGPHET, D. GLENNON, AND R. M. HUNT (2010): Mortgage market and the financial crisis: what triggers mortgage default. American Economic Review: Papers \& Proceedings, Vol. 100, pp. 490-494.

FOOTE, C. L., K. GERARDI, AND P. S. WILLEN (2008): Negative equity and foreclosure: Theory and evidence. Journal of Urban Economics, Vol. 64(2), pp. 234-245.

GERARDI, K., K. F. HERKENHOFF, L. E. OHANIAN, AND P. S. WILLEN (2013): Unemployment, negative equity, and strategic default. Federal Reserve Bank of Atlanta Working Paper Series, No. 2013-4.

GHENT, A. C., AND M. KUDLYAK (2011): Recourse and residential mortgage default: evidence from US states. Review of Financial Studies, Vol. 24(9), pp. 3139-3186.

GOODMAN, L. S., R. ASHWORTH, B. LANDY, AND K. YIN (2010): Negative equity trumps unemployment in predicting defaults. The Journal of Fixed Income, Vol. 19(4), pp. 67-72.

GROSS, D. B., AND N. S. SOULELES (2002): An empirical analysis of personal bankruptcy and delinquency. Review of Financial Studies, Vol. 15(1), pp. 319-347.

HAUGHWOUT, A., R. PEACH, AND J. TRACY (2008): Juvenile delinquent mortgages: bad credit or bad economy?. Journal of Urban Economics, Vol. 64(2), pp. 246-257.

HECKMAN, J. J. (1979): Sample selection bias as a specification error. Econometrica, Vol. 47(1), pp. 153-161.

HERKENHOFF, K. F., AND L. E. OHANIAN (2012): Foreclosure delay and US unemployment. Federal Reserve Bank of St. Louis Working Paper, No. 17.
IMF (2009): Republic of Estonia: Financial System Stability Assessment. IMF Country Report No. 09/89, Washington, March 2009, available at http://www.imf.org/external/pubs/cat/longres.aspx?sk=22768.0

JAPPELLI, T., M. PAGANO, AND M. DI MAGGIO (2013): Households' indebtedness and financial fragility. Journal of Financial Management, Markets and Institutions, Vol. 1(1), pp. 23-46.

JUDSON, R. A., AND A. L. OWEN (1999): Estimating dynamic panel data models: a guide for macroeconomists. Economics letters, Vol. 65(1), pp. 9-15.

KUKK, M., AND K. STAEHR (2013): The Over-Indebtedness of European Households: Updated Mapping of the Situation, Nature and Causes, Effects and Initiatives for Alleviating its Impact", Country Report Estonia, conducted for Directorate General Health and Consumers of the European Commission. Available at http://ec.europa.eu/consumers/financial_services/reference_studies_documents/docs/par t_2_synthesis_of_findings_en.pdf
KUKK, M. (2016): Debt Repayment Problems: What are the Implications for Consumption? Eesti Pank Working Paper Series, No. 1/2016.

KUKK, M. (2017): How does household debt affect financial asset holdings? Evidence from euro area countries. Studies in Economics and Finance, forthcoming.
KUMHOF, M., R. RANCIÈRE, AND P. WINANT (2015): Inequality, leverage, and crises. American Economic Review, Vol. 105(3), pp. 1217-1245.

MAY, O., AND M. TUDELA (2005): When is mortgage indebtedness a financial burden to British households? A dynamic probit approach. Bank of England Working Paper, No. 277.

MCCARTHY, Y. (2014): Dis-entangling the mortgage arrears crisis: The role of the labour market, income volatility and negative equity. Statistical and Social Inquiry Society of Ireland, Vol. 43, 2013-14, pp 71-90.
MERIKÜLL, J., AND T. RÕÕM (2016): The assets, liabilities and wealth of Estonian households: Results of the Household Finance and Consumption Survey. Eesti Pank Occasional Paper series, No. 1/2016.

MERIKÜLL, J., AND T. RÕÕM (2017): Financial fragility stress tests of Estonian households. Eesti Pank Working Paper series, No. 1/2017.

MIAN, A., K. RAO, AND A. SUFI (2013): Household balance sheets, consumption, and the economic slump. Quarterly Journal of Economics, Vol. 128(4), pp. 1687-1726.

MOCETTI, S., AND E. VIVIANO (2014): Looking behind mortgage delinquencies. Banca d'Italia, mimeo.

OECD (2009): OECD Economic Surveys: Estonia. The Committee on Financial Markets, Paris, October 2011. OECD Publishing, Paris. DOI: http://dx.doi.org/10.1787/eco_surveys-est-2009-en

OECD (2011): Estonia Review of the Financial System. The Committee on Financial Markets, Paris, October 2011. Available at http://www.oecd.org/finance/financialmarkets/49497930.pdf

SEMYKINA, A., AND J. M. WOOLDRIDGE (2010): Estimating panel data models in the presence of endogeneity and selection. Journal of Econometrics, Vol. 157(2), pp. 375-380.

SUTT, A., H. KORJU, AND K. SIIBAK (2011): The role of macro-prudential policies in the boom and adjustment phase of the credit cycle in Estonia. World Bank Policy Research Working Paper Series, No. 5835.
WOOLDRIDGE, J. M. (1995): Selection corrections for panel data models under conditional mean independence assumptions. Journal of Econometrics, Vol. 68(1), pp. 115-132.

## Appendix



Notes: The real debt volumes are expressed in EUR in 2005 prices



Notes: The real debt volumes are expressed in EUR in 2005 prices

Figure A.1. The dynamics of the volume and the penetration of housing loans and consumer loans from 2004:Q4 to 2011:Q4

Table A.1: Definitions of all the variables used in the empirical model with summary statistics for the indebted sample

| Variable | Definition | Mean | St. dev. |
| :---: | :---: | :---: | :---: |
| $D A_{\text {it }}$ | Dummy $=1$ if individual has arrears on debt at the end of quarter t , otherwise $=0$ | 0.018 | 0.131 |
| $\log y_{i t}$ | Logarithm of real inflow from legal entities to sight accounts of individual $i$ in quarter $t$, in EUR in 2005 prices | 7.297 | 0.768 |
| $\log y_{i t}^{\text {other }}$ | Logarithm of real inflow from sources other than legal entities to sight accounts of an individual $i$ in quarter $t$, in EUR in 2005 prices | 1.369 | 5.779 |
| DSR ${ }_{\text {a }}$ | Ratio of annual debt service payments to annual income in quarter $t$ | 0.314 | 0.323 |
| $D^{H} t o I_{i t}$ | Housing debt-to-yearly income ratio; debt stock is measured at the end of quarter $t$ and income is the sum of the income of the four previous quarters | 1.166 | 2.310 |
| $D^{C} t o I_{i t}$ | Consumer debt-to-yearly income ratio; debt stock is measured at the end of quarter $t$ and income is the sum of the income of the four previous quarters | 0.136 | 0.189 |
| FAtoI ${ }_{i-1}$ | Ratio of liquid financial assets to yearly income from legal entities at the end of quarter $t$. Financial assets include deposits, investment funds, stocks and bonds | 0.112 | 0.833 |
| $n e w D_{s}^{H}$ | Dummy $=1$ if individual has taken a new housing loan (owns a housing loan at the end of the quarter while not having any housing loan at the end of previous quarter), otherwise $=0$ | 0.005 | 0.072 |
| $a d d D_{s}^{H}$ | Dummy $=1$ if individual has taken an additional housing loan (the balance of the housing loan at the end of the quarter is larger than at the end of previous quarter), otherwise $=0$ | 0.012 | 0.109 |
| $n e w D_{s}^{C}$ | Dummy $=1$ if individual positive balance on consumer credit at the end of the quarter while the balance is zero at the end of previous quarter, otherwise $=0$ | 0.058 | 0.234 |
| $a d d D_{s}^{C}$ | Dummy $=1$ if individual has taken an additional consumer loan (the balance of consumer credit at the end of the quarter is larger than at the end of previous quarter), otherwise $=0$ | 0.304 | 0.460 |

Table A.2: Robustness check of estimation results for arrears on debt

|  | (1) | (2) | (3) | (4) | (5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| arrear $_{\text {it-1 }}$ | $\begin{aligned} & \hline 0.1849 * * * \\ & (0.0050) \end{aligned}$ | $\begin{aligned} & \hline 0.1869 * * * \\ & (0.0050) \end{aligned}$ | $\begin{aligned} & \hline 0.1884^{* * *} \\ & (0.0050) \end{aligned}$ | $\begin{aligned} & \hline 0.1885 * * * \\ & (0.0050) \end{aligned}$ | $\begin{aligned} & \hline 0.1896 * * * \\ & (0.0050) \end{aligned}$ |
| $\log y_{i t}$ | $\begin{aligned} & -0.0156^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0139 * * * \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0143 * * * \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0143 * * * \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0147^{* * *} \\ & (0.0004) \end{aligned}$ |
| $\log y_{t i t h e r}^{\text {ofer }}$ | $\begin{aligned} & -0.0011^{* * *} \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0010^{* * *} \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0009 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0009 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0009 * * * \\ & (0.0000) \end{aligned}$ |
| DSR ${ }_{w+1}$ | $\begin{aligned} & 0.0065 * * * \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & 0.0080^{* * *} \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & 0.0143 * * * \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & 0.0150 * * * \\ & (0.0008) \end{aligned}$ | .. |
| $D^{H}$ toI $_{i t-1}$ | $\begin{aligned} & 0.0006^{* * *} \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & 0.0005^{* * *} \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & 0.0001 \\ & (0.0002) \end{aligned}$ | .. | .. |
| $D^{c}{ }_{\text {col }}{ }_{i t-1}$ | $\begin{aligned} & 0.0075 * * * \\ & (0.0015) \end{aligned}$ | $\begin{aligned} & 0.0074 * * * \\ & (0.0015) \end{aligned}$ | $\begin{aligned} & 0.0031 * * \\ & (0.0015) \end{aligned}$ | .. | .. |
| FAtoI ${ }_{i k-1}$ | $\begin{aligned} & -0.0001 \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & -0.0007^{*} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0008^{*} \\ & (0.0004) \end{aligned}$ | . | .. |
| $I M R_{\text {it }}$ | $\begin{aligned} & -0.0081 * * * \\ & (0.0007) \end{aligned}$ | .. | .. | . | .. |
| Time dummies | Yes | Yes | No | No | No |
| No. of obs. | 1031625 | 1031625 | 1031625 | 1031625 | 1031625 |
| No. of groups | 65310 | 65310 | 65310 | 65310 | 65310 |
| $\mathrm{R}^{2}$ | 0.042 | 0.041 | 0.040 | 0.040 | 0.039 |

Notes: FE estimation of eq. (2) when explanatory variables are included one by one. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ***, ** and * indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

Table A.3: Estimation results for arrears on debt, sub-samples

|  | (1) <br> Male | (2) <br> Female | $\begin{gathered} (3) \\ \text { Age }<35 \\ \hline \end{gathered}$ | (4) Age 35-50 | $\begin{gathered} (5) \\ \text { Age }>50 \\ \hline \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\overline{\text { arrear }_{\text {it- }}}$ | 0.1832*** | 0.1862*** | 0.1807*** | 0.1941*** | 0.1734*** |
|  | (0.0075) | (0.0067) | (0.0069) | (0.0084) | (0.0142) |
| $\log y_{i t}$ | -0.0172*** | $-0.0142 * * *$ | $-0.0161^{* * *}$ | -0.0154*** | $-0.0146 * * *$ |
|  | (0.0007) | (0.0006) | (0.0006) | (0.0007) | (0.0011) |
| $\log y_{i t}^{\text {oher }}$ | -0.0010*** | $-0.0012^{* * *}$ | $-0.0015^{* * *}$ | $-0.0010^{* * *}$ | $-0.0005 * * *$ |
|  | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| DSR ${ }_{\text {w-1 }}$ | 0.0091*** | 0.0051*** | 0.0097*** | 0.0026* | 0.0079*** |
|  | (0.0016) | (0.0011) | (0.0015) | (0.0013) | (0.0021) |
| $D^{H}$ tol $_{i t-1}$ | 0.0007** | 0.0005* | 0.0006** | 0.0005 | 0.0007 |
|  | (0.0003) | (0.0003) | (0.0002) | (0.0004) | $(0.0009)$ |
| $D^{c}{ }_{\text {tol }}{ }_{i t-1}$ | 0.0095*** | $0.0064^{* * *}$ | 0.0061** | 0.0082*** | 0.0089*** |
|  | (0.0025) | (0.0019) | (0.0026) | (0.0023) | (0.0034) |
| FAtoI ${ }_{n-1}$ | -0.0001 | -0.0004 | -0.0003 | 0.0005 | -0.0006 |
|  | (0.0001) | (0.0010) | $(0.0003)$ | (0.0007) | $(0.0004)$ |
| $I M R_{\text {it }}$ | -0.0083*** | $-0.0076 * * *$ | -0.0093*** | $-0.0079 * * *$ | -0.0059*** |
|  | $(0.0012)$ | $(0.0010)$ | $(0.0013)$ | $(0.0012)$ | $(0.0015)$ |
| No. of obs. | 428513 | 603112 | 420782 | 428229 | 182614 |
| No. of groups | 27357 | 37953 | 26575 | 26196 | 12539 |
| $\mathrm{R}^{2}$ | 0.041 | 0.042 | 0.041 | 0.045 | 0.035 |

Notes: FE estimation of eq. (2). All other explanatory variables and time dummies are included in the estimations but not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are bootstrapped. Superscripts ${ }^{* * *}, * *$ and $*$ indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

Table A.4: Estimation results for linear probability model where dependent variable is a new or an additional consumer loan or a housing loan

|  | $\begin{gathered} \hline(1) \\ \text { New } \\ \text { consumer } \\ \text { loan } \end{gathered}$ | (2) Additional consumer loan | (3) <br> New housing loan | (4) <br> Additional housing loan |
| :---: | :---: | :---: | :---: | :---: |
| $\log y_{i t}$ | $\begin{aligned} & \hline-0.0040 * * * \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & -0.0092^{* * *} \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & \hline 0.0002^{* * *} \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & \hline 0.0004^{* * *} \\ & (0.0001) \end{aligned}$ |
| $\log y_{i t}^{\text {omer }}$ | $\begin{aligned} & 0.0002 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & 0.0005 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & 0.0000 \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & 0.0000 \\ & (0.0000) \end{aligned}$ |
| ${ }_{\text {DSR }}^{n+1}$ | $\begin{aligned} & -0.1249 * * * \\ & (0.0012) \end{aligned}$ | $\begin{aligned} & 0.1503 * * * \\ & (0.0025) \end{aligned}$ | $\begin{aligned} & -0.0124 * * * \\ & (0.0004) \end{aligned}$ | $\begin{aligned} & -0.0017^{* * *} \\ & (0.0005) \end{aligned}$ |
| $D^{H}$ tol $_{i t-1}$ | $\begin{aligned} & 0.0075 * * * \\ & (0.0002) \end{aligned}$ | $\begin{aligned} & -0.0101 * * * \\ & (0.0004) \end{aligned}$ | .. | $\begin{aligned} & -0.0006 * * * \\ & (0.0001) \end{aligned}$ |
| $D^{c}{ }_{\text {coI }}{ }_{i t-1}$ | .. | $\begin{aligned} & 0.0968^{* * *} \\ & (0.0040) \end{aligned}$ | $\begin{aligned} & 0.0152^{* * *} \\ & (0.0006) \end{aligned}$ | $\begin{aligned} & 0.0007 \\ & (0.0006) \end{aligned}$ |
| FAtoI ${ }_{\text {a }-1}$ | $\begin{aligned} & -0.0000 \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0001 * * * \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & -0.0000 \\ & (0.0000) \end{aligned}$ | $\begin{aligned} & 0.0000 \\ & (0.0000) \end{aligned}$ |
| No. of obs. | 2415123 | 2415123 | 2415123 | 2415123 |
| No. of groups | 107848 | 107848 | 107848 | 107848 |
| $\mathrm{R}^{2}$ | 0.016 | 0.011 | 0.003 | 0.002 |

Notes: Notes: FE estimation of eq. (2). All other explanatory variables and time dummies are included in the estimations but not reported. Standard errors are reported in parentheses below the coefficient estimates, SE estimates are robust to disturbances that are heteroskedastic and autocorrelated. Superscripts ***, ** and * indicate that the coefficient is statistically different from 0 at the $1 \%, 5 \%$ and $10 \%$ level respectively.

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Nicolas Reigl. Forecasting the Estonian rate of ilnflation using factor models


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[^1]:    ${ }^{1}$ Source: Eurostat database at http://ec.europa.eu/eurostat/data/database. Further details from the author upon request.

[^2]:    ${ }^{2}$ There is household level data available from Household Finance and Consumption survey by Eesti Pank but the data are cross-sectional and originate from 2013.

