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THE FINANCIAL FRAGILITY OF ESTONIAN HOUSEHOLDS: EVIDENCE FROM STRESS TESTS ON THE HFCS MICRODATA

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The financial fragility of Estonian households: Evidence from stress tests on the HFCS microdata

Jaanika Meriküll and Tairi Rõõm *

Abstract

This paper analyses the financial fragility of the Estonian household sector using microdata from the Household Finance and Consumption Survey (HFCS). We use a stress-testing framework where the probability of default is evaluated on the basis of the financial margin (i.e. the ability to service debt from current income) and the availability of financial buffers. The HFCS data from household interviews are complemented with information from administrative registers. This lets us evaluate and compare measures of financial vulnerability that draw on data from different sources. We derive a set of indicators to identify households that are financially distressed and analyse the sensitivity of financial sector loan losses to adverse shocks. The stress-test elasticities are assessed separately for three standardised negative macroeconomic shocks: a rise in interest rates, an increase in the unemployment rate, and a fall in real estate prices. In addition, we evaluate the impact of a simultaneous shock mimicking the dynamics of these three variables during the Great Recession. It is found that: (1) despite there being a lot of households with financial difficulties, the risks for banks from the household sector are limited; (2) financial fragility is strongly negatively related to income; (3) the loan default rate of households is most sensitive to shocks to the unemployment rate and the interest rate, while the loan losses of banks are affected most by real estate price shocks; and (4) compared with the survey data, the information collected from administrative sources points to higher household default rates and larger bank losses.

JEL Codes: D14 (household saving: personal finance); E43 (interest rates: determination, term structure, and effects); G21 (banks, depository institutions, micro finance institutions, institutional investors)
Keywords: household financial fragility, stress-testing, household finance and consumption survey, Estonia, measurement error in household surveys

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Non-technical summary

This paper assesses the financial fragility of the Estonian household sector. We employ a set of stress-testing models in which the probability of default on loans is evaluated on the basis of households' financial margins. The analysis employs micro-level data from the Estonian Household Finance and Consumption Survey (HFCS), which was conducted from March to June 2013. In addition to survey-based variables we use data from administrative registers, which lets us compare risk assessments originating from different data sources.

Probability of default is assessed by comparing the debt service payments of each household with its current income and stock of liquid assets. When household's debt servicing costs exceed its disposable monthly income and the calibrated level of liquid assets then it is assigned a non-zero probability of default. The threshold level of liquid assets is calibrated so that the aggregate probability of the default rate matches the share of non-performing loans in the Estonian banking sector during the survey period.

We derive a set of indicators to identify households that are financially distressed and analyse the sensitivity of financial sector loan losses to adverse shocks. This is the first paper that provides a comprehensive assessment of the financial vulnerability of the Estonian household sector and compares the indicators of financial fragility based on the survey and on administrative data.

The paper identifies a number of findings. First, a relatively large number of Estonian households were financially distressed in 2013, but despite the high level of household distress the resulting loan losses from the household sector for commercial banks were small. This is an unexpected finding, given that not only was the share of households whose income was below expenditures rather large, but indebted households also had small financial buffers. Evidently households had to rely on other sources of finance besides their personal income and liquid assets to overcome their financial distress.

The HFCS contains questions that aim to shed light on how households cope with financial difficulties. The responses to these questions indicate that Estonian households are more reliant on social networks than euro area households are on average. Almost half of Estonian households (45%) reported that they would be able to get financial help from relatives or friends, while the corresponding share was about half as much in the euro area. On the other hand, reliance on short-term financing was less prevalent in Estonia than in the euro area, as 10% of households in Estonia would use credit card debt and 5% would try to get other loans if they had debt servicing problems, while the equivalent figures were 23% and 15% in the euro area.

Second, comparison with the administrative data indicates that Estonian households tend to overestimate their income and assets and underestimate their loan burden in the survey. We experimented with replacing the survey data with register data for household income, debt and assets, first one by one and then for all these variables together. The use of register data resulted in larger estimated household default rates and larger losses for the banks than were found with the survey-based measures. However, the assessments based on the data from administrative sources did not alter the main conclusion that the estimated loan losses for banks from the household sector were modest.

Third, the stress-test elasticities of household default rates and banking sector loan losses were assessed separately for three standardised negative macroeconomic shocks: a rise in interest rates, an increase in the unemployment rate, and a fall in real estate prices. The stress-testing of Estonian households implied that shocks to unemployment and interest rates were the main source of household distress, while losses for the banking sector were highest from real estate price shocks.

Shocking the interest rates and the unemployment rate resulted in only mild changes in the probability of households defaulting and the loss given default of the banks. Increases in the probability of default were somewhat stronger in response to the unemployment rate shocks, which is a similar finding to that for other Central and Eastern European countries where job losses generally result in a larger drop in income than in Western European countries.[1]

By construction, the real estate price shocks have no effect on the probability of default and only affect the loss given default rates of the banks. Although a decline in real estate prices had a stronger effect on estimated loan losses than the interest rate and unemployment rate shocks did, the impact was still rather mild. This is a surprising finding, given the large historical variation in Estonian real estate prices, which meant that the shocks of one, two and three standard deviations that were applied led to very strong declines in house prices of 24%, 49% and 73% accordingly. The stress testing results were confirmed by the aggregate historical dynamics of the financial stability indicators in Estonia, which also showed that the Estonian banking sector experienced low loan loss provision (LLP) rates and almost negligible write off rates throughout the recent financial crisis.

In the second stage of the stress-testing evaluation we estimated the impact of a simultaneous shock to all three above-named variables, which mimicked their movements during the Great Recession period covering the ten quarters starting from the first quarter of 2008. The resulting increases in the non-performing loan (NPL) rate and the loss given default rate were somewhat milder than the actual historical increases in the NPL and LLP rates in this period. The effect from the model was more stable than the historic trends of these variables because households were on average more financially solvent in 2013 than during the crisis. In addition, our simulation model is not dynamic and so it is better suited for assessing the effects of short-lived shocks.

Fourth, the household characteristics that were most correlated with financial fragility were income and education. We assessed the financial fragility across different household types. Household income was strongly negatively related with the probability of default as households in the first and second income quintiles were substantially more likely to default on their loans than more affluent households were. This result was confirmed by multivariate analysis, which also showed a significant negative link between income and various measures of the probability of default. The education level of the household reference person also played a role, as a higher level of education resulted in fewer problems with loan servicing.

Fifth, we assessed the relevance of cyclical effects for the estimated probability of default. This was evaluated by using the loan origination years as control variables in regressions where the dependent variables were various indicators of the probability of default. The estimation results showed that loans issued in the years 2006–2009 were associated with a higher rate of self-reported loan repayment problems. However, regressions on three alternative measures of the probability of default did not identify significant cyclical variations in the quality of the loans issued.

[1] The related findings are discussed in Galuscak et al (2016) and Johansson and Persson (2006).

Contents

1. Introduction

Household borrowing has increased considerably in most European countries in recent decades, both in absolute terms and in relation to household income. This has raised concerns among central banks about the increasing financial vulnerability of the household sector and the possible consequences of increased indebtedness for the stability of the financial system.[2] The fragility of the financial sector has traditionally been assessed using aggregate indicators, but the scope for using aggregate data is limited because such data do not allow the distributions of debt and asset holdings to be evaluated or the financial buffers of indebted households to be assessed. Given the inherent limitations of risk assessments based on aggregate data, central banks have gradually increased their reliance on micro data for evaluating the financial vulnerability of households.

As part of the initiative to base financial stability analysis on disaggregated data, the euro area central banks together with the ECB launched the Household Finance and Consumption Survey (HFCS) to collect data on households' assets and liabilities in a harmonised manner. The first wave of the survey was conducted between 2008 and 2011 and the second took place in 2013–2014. It is planned that the future waves will be run at three-year intervals. This gives the central banks access to micro-level data that are representative at both the national and euro area levels and contain comprehensive information on households' balance sheets.

The availability of the HFCS data makes it possible to conduct household stress tests by quantifying the impact of various adverse shocks on net wealth and by assessing the ability of households to continue servicing their debts after they have been exposed to shocks. Several central banks have performed household stress tests using the HFCS data or similar micro-level datasets.[3]

The current study uses the stress tests to assess the financial fragility of Estonian households, employing the Estonian HFCS from 2013. The methodology used consists of the following steps. First, financially vulnerable households are identified. In the baseline definition, these are households whose disposable income is lower than their basic consumption expenditures and debt servicing costs. Second, the probability of default (PD) is estimated for indebted households by considering their financial vulnerability and the size of their financial buffers. Third, the exposure at default (EAD) is assessed by evaluating the weighted average share of defaulting loans in the total loan stock. Fourth, the share of banks' loan losses in the total stock of loans, or the loss given default (LGD), is calculated, bearing in mind that banks can alleviate the losses caused by non-performing loans by selling the collateral assets. Finally, households are subjected to various adverse macroeconomic shocks and the consequent changes in PD, EAD and LGD are evaluated.

Our stress testing methodology is closest to that used in the study by Ampudia et al. (2016b). In particular, we follow their idea of calibrating the probabilities of default for households so that the micro-data based exposure at default matches the aggregate historical share of non-performing loans (NPL) in the banking sector. We assess the vulnerability of

[2] It has been found that the rapid increase in household debt was one of the triggers of the Great Recession, see e.g. Mian and Sufi (2010).

[3] Examples of such studies include Johansson and Persson (2006) for Sweden, Herrala and Kauko (2007) for Finland, Holló and Papp (2007) for Hungary, Albacete and Fessler (2010) for Austria, Faruqui et al. (2012) for Canada, Martinez et al. (2013) for Chile, Michelangeli and Pietrunti (2014) for Italy, Banbula et al. (2015) for Poland, Bilston et al. (2015) for Australia, Ampudia et al. (2016) for 10 euro area countries, and Galuščák et al. (2016) for Czechia.

households to adverse shocks to interest rates, unemployment and real estate prices. The impact of these shocks is evaluated first separately and then simultaneously, with the simultaneous shock constructed so that it mimics the aggregate movements in these three variables in Estonia during the Great Recession in 2008–2009.

The survey data of the Estonian HFCS were complemented by data collected from various registers and from financial institutions. This allows the analysis from the survey data to be compared with estimations of financial vulnerability based on the register data, providing valuable insights into how much the assessments based on alternative data sources vary and whether the use of the survey data can lead to biased estimations of household sector risks.

Estonia is an interesting case study for assessing the financial fragility of households, since the accumulation of debt occurred extremely fast during a concentrated period that spanned only a few pre-crisis years. The level of household debt was modest until the beginning of the current century, because there was essentially no market for housing loans in Estonia in the 1990s. The next ten years saw remarkably rapid developments, as the credit stock of households grew by more than 50% a year from 2001 until the global financial crisis, peaking in 2006 and 2007. By 2008, the ratio of household credit to GDP reached 50%, which is similar to the euro area average.[4] On the demand side, this very fast increase in household credit occurred because of changing income expectations when Estonia joined the EU in 2004. On the supply side, it was the result of intensified competition for market share among the commercial banks during the boom years preceding the Great Recession.

The paper is structured as follows. The second section describes the Estonian HFCS data used for the analysis. The third section presents the financial burden and financial fragility indicators of Estonian households in comparison to those of other euro area countries. The fourth section focuses on the derivation of the measures of financial fragility for households that are used in the stress tests. The fifth section presents the results of the stress testing exercises and the sixth section provides the conclusions.

2. The data

The HFCS dataset contains detailed household-level data on various items of household balance sheets together with related demographic and economic variables, including various types of income, employment status, inheritances and gifts, consumption, etc.

The fieldwork of the Estonian HFCS took place between March and June 2013 and the sample contained 2220 households. The sampling design was one-stage stratified systematic sampling. Ten strata were defined by the cross-section of five NUTS3 regions and two income groups (the highest income decile and the rest). The two income groups were divided using the income data collected from various registers for the 2011 calendar year. Wealthy households were oversampled in the survey to give better coverage of households' assets. Since no register data on wealth were available, the oversampling was based on income, so that 20% of the sample was selected from the highest income decile and 80% from the rest of the population.

The estimation weights were calculated to adjust for survey non-response and were calibrated for age, sex, degree of urbanisation, ethnicity, education, household size and home

[4] Meriküll and Rõõm (2016) discuss the development of the household credit market in Estonia since the early 2000s and Meriküll (2015) provides a comparative view against other EU and OECD countries.

ownership status. Replicate weights were introduced for variance estimation, and bootstrap methods with replacement were used to create 1000 replication weights. Multiple stochastic imputation was used to fill in the data for missing observations. The imputation was not applied to the whole survey, but the key variables, such as the components of net wealth, income and consumption, were imputed. Five implicates were created based on the assumption of "missing at random". The methodology for calculating the weights and for the imputation was similar to that used in other euro area countries participating in the HFCS, see Eurosystem Household Finance and Consumption Network (2013a) for more details.

A more detailed explanation of the sample statistics of the Estonian HFCS is given in Meriküll and Rõõm (2016).

3. The financial burden of Estonian households

Before evaluating the financial fragility of households on the basis of the financial margin and the associated probability of default, we provide an overview of some alternative measures of financial fragility that have also been used frequently in the literature as indicators of potential financial stress. We focus on four measures of the financial burden: the debt-to-income ratio, the debt-to-asset ratio, the debt-service-to-income ratio and the loan-to-value ratio of household main residences, or the DTI, DTA, DSTA and LTV ratios. In addition we evaluate the level of financial buffers, which households hold in the form of liquid assets that can be accessed in the event of an adverse shock. This is measured by the net-liquid-assets-to-income ratio (NLATI ratio). The definitions for all these ratios are given in Appendix 1.

We employ household-level data from the HFCS for the analysis. The estimated measures of financial fragility for Estonia are obtained from the Estonian HFCS dataset. The figures for the other euro area countries come from two sources. Financial burden measures that do not rely on income are taken from the report by the Eurosystem Household Finance and Consumption Network (2013) on the results of the first wave of the HFCS. As this report only covers measures that are based on gross income, we use the study by Ampudia et al (2014) as an alternative source for the financial burden ratios derived from net disposable income.[5]

All measures of financial fragility are estimated for the subgroup of households that have debts. We provide the median estimates and compare the Estonian values with those for other euro area countries. In addition to cross-country comparisons of measures of financial fragility we also conduct multivariable analysis to assess which households are more exposed to potential financial stress and to evaluate whether the fragility indicators vary depending on when in the credit cycle the loans were taken. The estimated regression results are provided in Table A2 in Appendix 2.

[5] The measure of financial buffers – the net-liquid-assets-to-income ratio – is estimated for gross income since this ratio is not covered by Ampudia et al (2014) and we do not have comparable estimates based on net income for other countries.

3.1. The debt-to-asset ratio, debt-to-income ratio, and debt-service-to-income ratio

In this subsection we take a closer look at three financial burden indicators: the debt-to-asset, debt-to-income and debt-service-to-income ratios. Our first measure of financial pressure, the DTA ratio, is constructed by dividing the total value of outstanding debt by total assets and is a yardstick of a household's solvency. The DTI and DSTI ratios provide information on the capacity of households to service their debts from income. DSTI measures the level of current monthly debt payments against monthly net income and is an indicator of the short-term ability of households to repay their debts on time. DTI shows how many years a household will need to generate income for in order to repay its entire debt and can be considered a longer-term measure of the capacity to pay off the debts.

Although the three measures assess the financial fragility of households from different angles, their evaluation for Estonia yields similar implications. The median values of these indicators across the euro area countries are shown in Figures 1–3.[6] The comparison of the Estonian DTI, DTA and DSTI ratios with those of the other euro area member states implies that the financial burden of Estonian households is relatively modest, as the median values of all three indicators of the financial burden are lower than those in the euro area. The level of indebtedness of Estonian households is moderate for two main reasons: 1) The relatively recent development of the household credit market, and 2) the privatisation of household dwellings in the 1990s.

Household credit has generally expanded in most developed countries in recent decades. Several CEE countries, including Estonia, have also witnessed credit deepening but it has happened more recently in this region. The increase in the credit burden of households, although being very rapid during the boom years, has mostly occurred since the early 2000s in Estonia. This means that the financial burden of households is still relatively modest and it generates substantial generational differences in the credit burden. The bulk of household debt consists of real estate loans with long maturities, which were not available to households in older cohorts. In addition, older households were able to obtain their houses or apartments through privatisation in the 1990s, which enabled them to buy their dwellings at a very low cost.[7] That meant they did not need to use credit for home purchases, so older Estonian households mostly have only non-collateralised debts and a lower overall credit burden than younger households do.[8] The modest level of household debt in the older generation also affects the average for the whole population and as a result, Estonian households are less indebted than euro area households on average.

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[6] The group of euro area countries consists of the fifteen countries that participated in the first wave of the HFCS; see the report by Eurosystem Household Finance and Consumption Network (2013) for details. Some graphs also exclude Finland since some of the variables needed for estimating the financial burden indicators are missing in the Finnish HFCS dataset.

[7] Privatisation worked through vouchers, which could be obtained for work tenure, for raising children, etc. Most households could purchase their dwellings entirely using the vouchers at no cost, while others had to buy additional vouchers from the market to complete the transactions, but their price was generally very low.

[8] The distribution of the financial burden across households in different cohorts in Estonia is presented in Meriküll and Rõõm (2016).

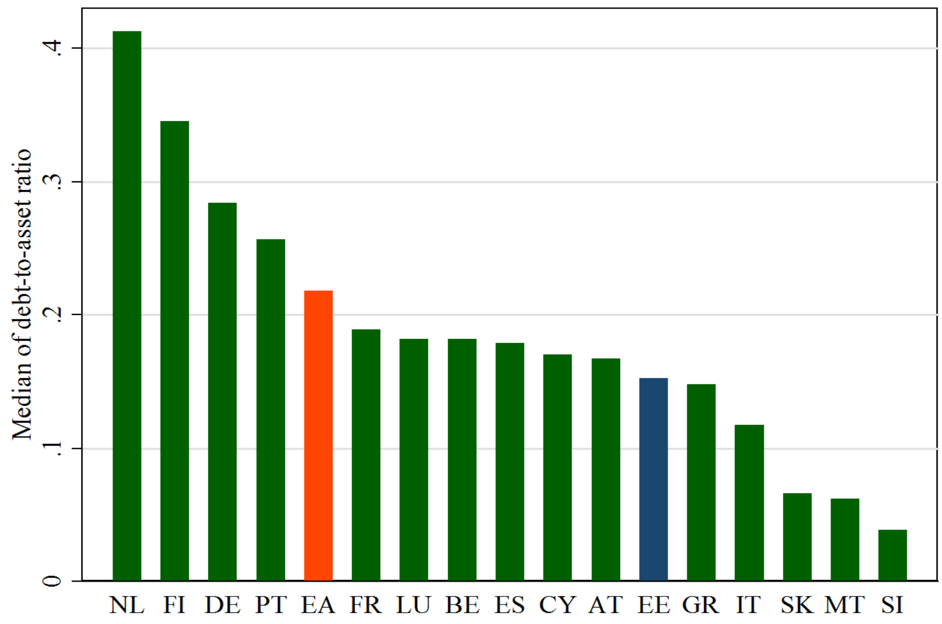

Figure 1: Median debt-to-asset ratio in Estonia and in the euro area

Sources: Authors' calculations for Estonia; the Eurosystem Household Finance and Consumption Network (2013) for the other countries.

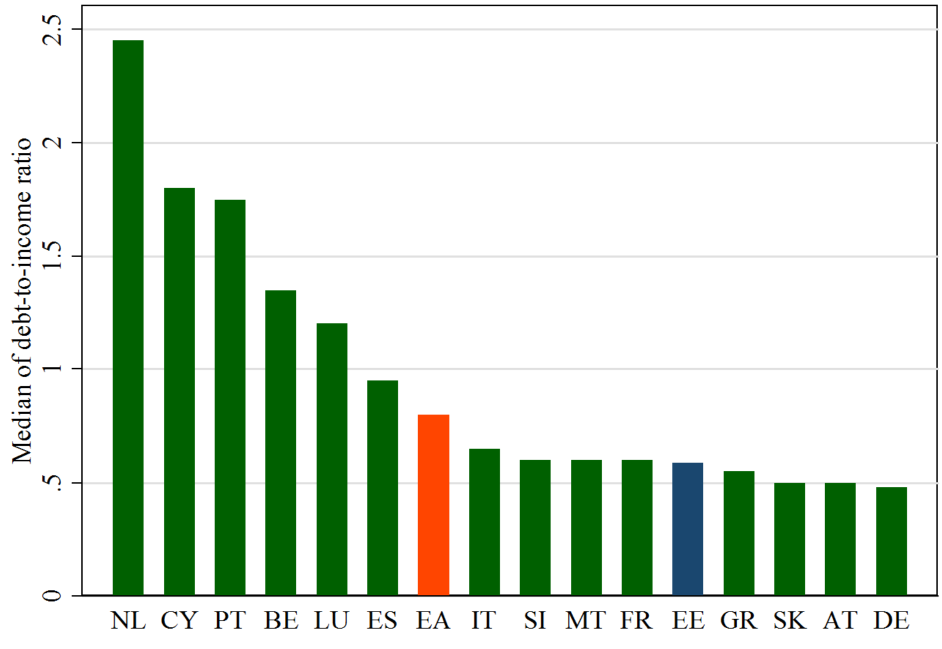

Figure 2: Median debt-to-income ratio in Estonia and in the euro area

Notes: Income refers to net annual income.
Sources: Authors' calculations for Estonia; Ampudia et al. (2014) for the other countries.

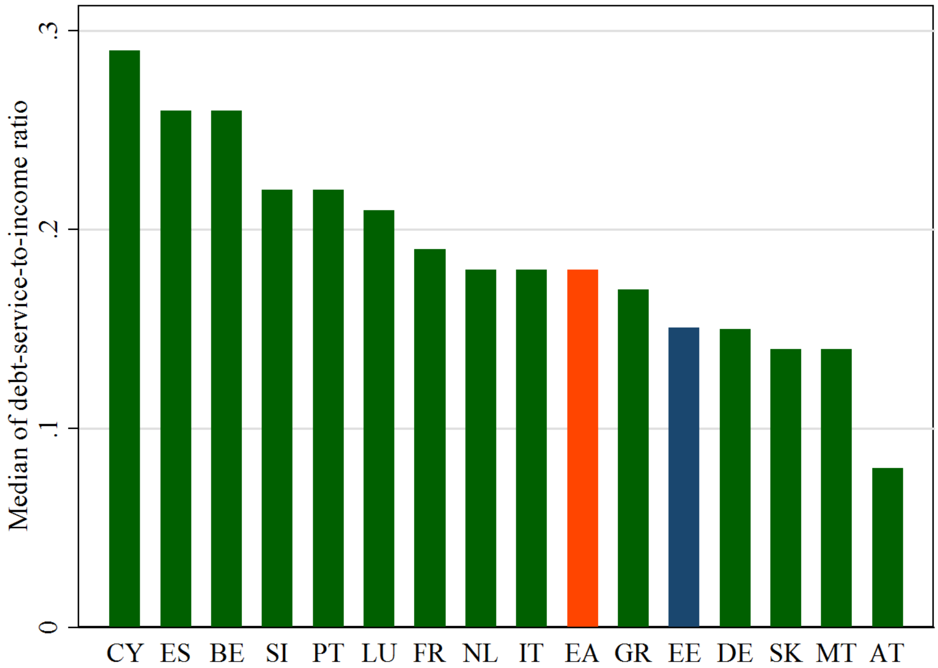

Figure 3: Median debt-service-to-income ratio in Estonia and in the euro area

Notes: Debt service costs refer to monthly debt servicing costs and income to average monthly net income.
Sources: Authors' calculations for Estonia; Ampudia et al. (2014) for the other countries.

Regression analysis is used to assess the variation in the financial burden across households with different characteristics. We run OLS regressions with the logarithms of the DTA, DTI and DSTI ratios as the dependent variables for a subset of households that have debts (i.e. we exclude the ratios with zero values from the regressions). The dependent variables are taken to the logarithmic form to achieve a better fit of the estimations. (The distribution of indicators is positively skewed.) We use multiply imputed data with five implicates and 1000 replicate weights for estimating standard errors.

The results of the estimations are presented in Table A2 in Appendix 2. The first implication from the regressions is that indebted households in the lowest income quintile have a significantly larger financial burden (higher DTI and DSTI ratios) than the rest of the households. The DTI and DSTI ratios also decrease monotonically across income quintiles. However, the DTA ratio does not vary significantly with income.

The age of the household reference person tends to be negatively related with the financial burden (DTA and DTI ratios), but the results are not significant for all age groups and there is no significant relationship between age and the DSTI ratio.

It is also worth highlighting that those households which do not have non-collateralised loans generally have a lower financial burden. Interestingly, having more than one mortgage is negatively related with the debt burden relative to income. This may indicate that only high-income households are able to obtain multiple real estate loans in Estonia.

We also assess how the financial burden indicators vary depending on the year when the largest loan was taken. The estimated coefficients for the DTA ratio across the years become significantly positive from 2005 and have a hump-shaped pattern peaking in 2007. From 2009 onwards they become insignificant. Absent the cyclical effects, the DTA ratio should increase across the years since the more recently the loans were issued, the smaller the amount of the principal that has been paid back. That we observe the hump-shaped pattern across the years for the estimated coefficients is indicative of the credit cycle effects for household loans. Estonia experienced a strong real estate boom and bust cycle with real estate prices reaching their maximum level in 2007 and contracting by 50% in the following crisis. The inflated DTA ratios for the years 2005–2008 are the legacy of this boom and bust cycle.

The DTI and DSTI ratios also become significantly positive from 2005 onwards but do not exhibit such a strong hump-shaped pattern as the DTA ratio does. In addition, their maximum coefficient estimates do not coincide with the peak of the boom in 2007. Instead, the DTI ratio has higher values in 2006, 2010 and 2013 and the DSTI ratio peaks in 2009. A hump-shaped pattern coinciding with the credit cycle for the DTI and DSTI ratios would indicate that banks relaxed their lending policies during the boom years. That we do not observe this for Estonia implies that income-related constraints for borrowing were not substantially altered by the banks throughout the cycle.

3.2. Loan-to-value ratio of the household main residence

Unlike the other indicators of the financial burden, which have below-average values in Estonia, the median value of the LTV ratio of the household main residence (HMR) is relatively high (Figure 4). The level of this ratio is one of the highest in the euro area countries, coming in at third highest behind the Netherlands and Finland. The high level of the LTV ratio is caused by the recent credit market cycle. The bulk of the mortgage loans were issued in the boom years of 2005–2007, when real estate values were high. Estonia experienced a more amplified cycle in the real estate market than did most of the other euro area countries, which resulted in high loan-to-value ratios after the crisis. The LTV ratio of the main residence was above 100% for 8.9% of households in 2013 (Meriküll and Rõõm (2016)).

We also run the regression with the logarithm of the LTV ratio as a dependent variable, and the regression results are presented in Table A2 in Appendix 2. The estimated effects are similar to the findings for the other financial burden indicators, and especially to the DTA ratio, which is not surprising since the household main residence makes up the largest share of the assets of households (the average share of the HMR in total assets was 56% in Estonia, see Meriküll and Rõõm (2016)). There are only a few differences vis-a-vis the results for the DTA ratio. First, whether households have non-collateralised loans or not and whether they have one or more mortgages makes no significant difference to the LTV ratios. Second, households where the reference person is self-employed rather than salaried tend to have higher LTV ratios.

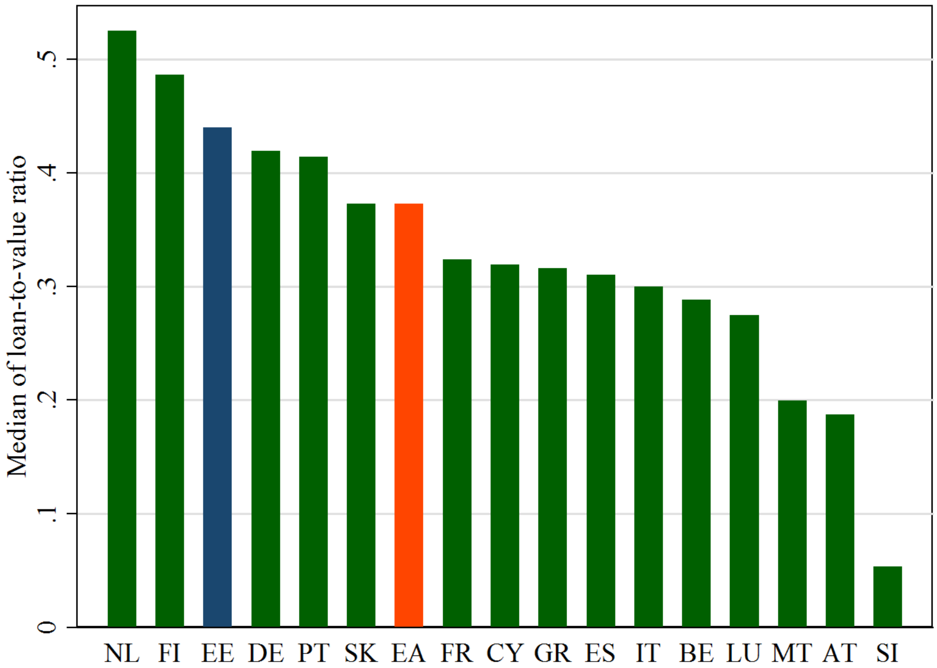

Figure 4: Median loan-to-value ratio of the household main residence in Estonia and in the euro area

Sources: Authors' calculations for Estonia; the Eurosystem Household Finance and Consumption Network (2013) for the other countries.

3.3. Net-liquid-assets-to-income ratio

The net-liquid-assets-to-income ratio measures the extent of the financial buffers that households can use if they face adverse shocks to income or expenses. It is often used in the literature as an indicator of financial stress that complements measures of the financial burden. It is also directly related to the analysis of household stress tests that we concentrate on in the following sections of the paper since the probability of the household defaulting on loans is negatively related to the amount of net liquid assets it owns, ceteris paribus.

An overview of the NLATI ratios for the euro area countries, including Estonia, is presented in Figure 5. In contrast to the DTI and DSTI ratios, the value of net liquid assets is assessed relative to gross income.[9] Figure 5 shows the median NLATI ratios for the whole population of households and for the subgroup of indebted households. Both of those figures are substantially below the euro area medians in Estonia, but the NLATI ratio is especially low for the subgroup of indebted households. Among the whole population of households in Estonia the median of the NLATI ratio is 9.8% while for the subgroup of indebted households it is 3.0%. The corresponding ratios for the euro area are 18.6% and 14.6%. The only two euro area countries with lower NLATI ratios for indebted households than Estonia are Greece and Slovenia.

[9] The reason for using gross income in this case is that the net disposable income for other euro area countries is not available and the NLATI ratio is not covered in the study by Ampudia et al (2014) which we use as the source for other financial fragility indicators for the euro area countries.

We also calculated the NLATI ratio relative to net disposable income in Estonia. Since the denominator of this ratio is lower for net income than for gross income, the median of NLATI is about 40–50% higher when it is based on net income and is 14% for the whole population of households and 4.6% for the households with debt. As noted before, comparative figures for other euro area countries are not available.

The upshot of this finding is that although the financial burden of Estonian households is relatively modest in comparison to the euro area, the level of financial buffers that households can rely on if they are exposed to negative shocks is also low, which increases their financial fragility. The analysis of household stress tests, which takes comprehensive account of the ability to pay debts out of income and the extent of the net liquid assets households have, is given in the following sections of the paper.

The regression estimates, which show the variation in the NLATI ratio across households with different characteristics, are shown in the last column of Table A2 in Appendix 2. The estimations were only carried out for the subgroup of indebted households as we were mainly interested in the conditional distribution of liquid buffers for indebted households. Some results are worth highlighting. First, the estimated coefficients are negative and decreasing across income quintiles, indicating that households' level of net liquid assets increases less than proportionally with the level of income. Second, the NLATI ratio is increasing across the net wealth quintiles. Third, the ratio of net liquid assets to income is not related to age, as households have similar liquidity buffers relative to their income across the age groups.[10] Fourth, there is a significant positive relationship between the NLATI ratio and the level of education of the household reference person. (Note that this result holds after controlling for the income and net wealth level.) The finding of a positive correlation between education and the extent of the financial buffers that households have could stem from various causes, notably that more educated households may be more patient, more risk-averse or more financially literate. All these factors should contribute positively to the buffer stock of liquid financial assets. As a consequence, it can be argued that less educated people are more financially fragile, not only because they have a lower level of financial buffers but also because they are more exposed to negative income shocks. (The exposure stems from differences in unemployment: since the unemployment rate is higher for labour market participants with a lower education level, they have a higher probability of becoming unemployed and experiencing a negative income shock.)

[10] Note that for the whole population of households the NLATI ratio is strongly dependent on age, as households where the reference person has reached retirement age tend to have larger financial buffers relative to their income. Given that there is a strong dependency on age in general, it is interesting to observe that it is not significantly related to the NLATI ratio for the subgroup of indebted households.

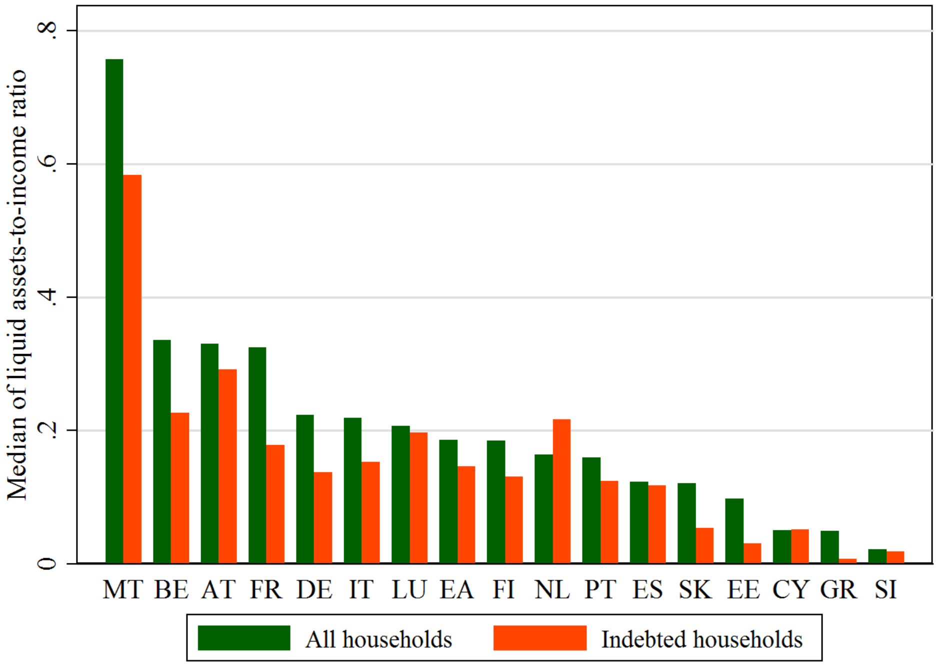

Figure 5: The median net-liquid-assets-to-income ratio in Estonia and in the euro area

Notes: Income refers to annual income and is measured in gross terms as the liquid assets to net income ratio is not available for other euro area countries.
Sources: Authors' calculations for Estonia; the Eurosystem Household Finance and Consumption Network (2013) for the other countries.

4. Derivation of the measures of household financial fragility that are used in the stress tests

4.1. The household financial margin, the probability of default and the banks' loss given default: baseline measures

In this subsection we derive the measures of household financial fragility that are used in the stress tests. First, we define the household financial margin (FM), then we show how the household probability of default is calculated on the basis of the FM and the liquid assets the household holds. The probability of default (PD) is calibrated to match the aggregate household sector ratio of non-performing loans (NPL). Finally, a measure of banking sector losses is defined, which provides an estimate of the impact of household sector loan quality on financial stability.

The household financial margin is derived as follows:

$$FM_i = Y_i - DP_i - C_i \tag{1}$$

where FM_i denotes the financial margin of household i, Y_i is total disposable income, DP_i is total debt service costs and C_i is essential consumption. Total disposable income covers the after-tax income of all household members from all sources, i.e. labour income, capital income, pensions, and any other public or private transfers. Income is collected for the previous calendar year (2012) and is divided by 12 to obtain average monthly income. The data are collected in gross terms and converted to net terms using statutory tax rates and exemptions.[11] Debt payments consist of monthly payments for mortgages and other loans; other loans are all consumer loans and loans from employers or other households, except leases, credit line overdrafts and credit card debt.[12] The reference period is the time of the survey and payments cover only interest and loan principal payments, but do not cover insurance, taxes or other fees.

Essential consumption or basic consumption has been defined as the Statistics Estonia official estimate of the subsistence minimum (Statistics Estonia, Table hh27 at stat.ee). The subsistence minimum without expenditures on housing was 128 euros for single person households in 2013. The subsistence minimum for households with more than one member is calculated by multiplying this amount by the sum of consumption weights taken from the OECD equivalence scale.[13] We add the monthly rental payments to the subsistence minimum to calculate the total level of basic consumption for renters.

Authors of earlier studies have taken various approaches to defining essential consumption, with some defining it as the subsistence minimum or poverty line (Bilston et al. (2015), Ampudia et al. (2016)), or as the household self-reported minimum subsistence level (Albacete and Fessler (2010)), and some defining it more generously as consumption of food, energy, health and rent (Galuščák et al. (2016)) or the minimum non-durable consumption and non-interest housing costs (Johansson and Persson (2006)). We prefer to use the subsistence minimum instead of the actual expenditures on the most essential consumption categories because it is likely that consumption is reduced in response to negative shocks and households can be expected to reduce their expenditures to the subsistence level before defaulting. Alternative measures of consumption are used as robustness tests in the next subsection.

Figure 6 presents the distribution of the financial margin that is calculated using our baseline definition. Households are split into four groups: debtless households, households with only mortgage debt, households with both mortgage and non-collateralised debt, and households with only non-collateralised debt. The indebted households have a negative financial margin more frequently than debtless households do, as the share of households with a negative financial margin is 13.0% for indebted households and 7.1% for debtless households (the financial margin for the subset of indebted households including all debt types is not reported in Figure 6, but is in Table 1 column (2)). The distribution of the financial margin differs substantially between debt types. As much as 18.9% of households with only non-collateralised loans have a negative financial margin, while among households who have collateralised loans this share is 11% and among households with both types of debt it is 4.5%. The distribution of the financial margin is significantly different for households with

[11] Although the Estonian tax system is relatively simple with a flat tax rate and only a few tax exemptions, several assumptions are still required for disposable income to be derived from all the income types at the household level. It is assumed that the tax-exempt amount for total income and the additional exemption for retired persons apply, and various deductions have been assumed, including exemptions for household main residence mortgage interest payments, children, and investments in voluntary pension schemes. It is also assumed that no income taxes are paid on rental income or on self-employment income from abroad as tax evasion is common for these income types. Married couples are assumed to submit joint income declarations. The household member with the highest income is assumed to declare the household-level income and to deduct all the household-level deductibles in households with no married couple.

[12] Leases, credit card debt and bank account overdrafts are excluded because the data on monthly payments for these loans are not available in the HFCS. The exclusion of these loans should not have a major impact on the results since the majority of the loan burden in Estonia consists of mortgages, and collateralised loans make up 95% of the total loan burden excluding leases.

[13] The first adult household member gets a weight of one, each subsequent household member who is at least 14 years old gets a weight of 0.5, and each household member aged less than 14 gets a weight of 0.3.

mortgages and for other households (including households with no debt or with non-collateralized debt only). For households with mortgages the mean and median values of the financial margin are substantially higher than they are for other households (Table A3 in Appendix 3). In general, the values of the financial margin across different percentiles tend to be higher for mortgage holders, with the exception of low percentiles (up to 20th percentile) where debtless households have a higher financial margin. This result is in line with the previous findings on Estonian data indicating that mortgage debts are concentrated to high-income households in Estonia (Meriküll and Rõõm (2016)).

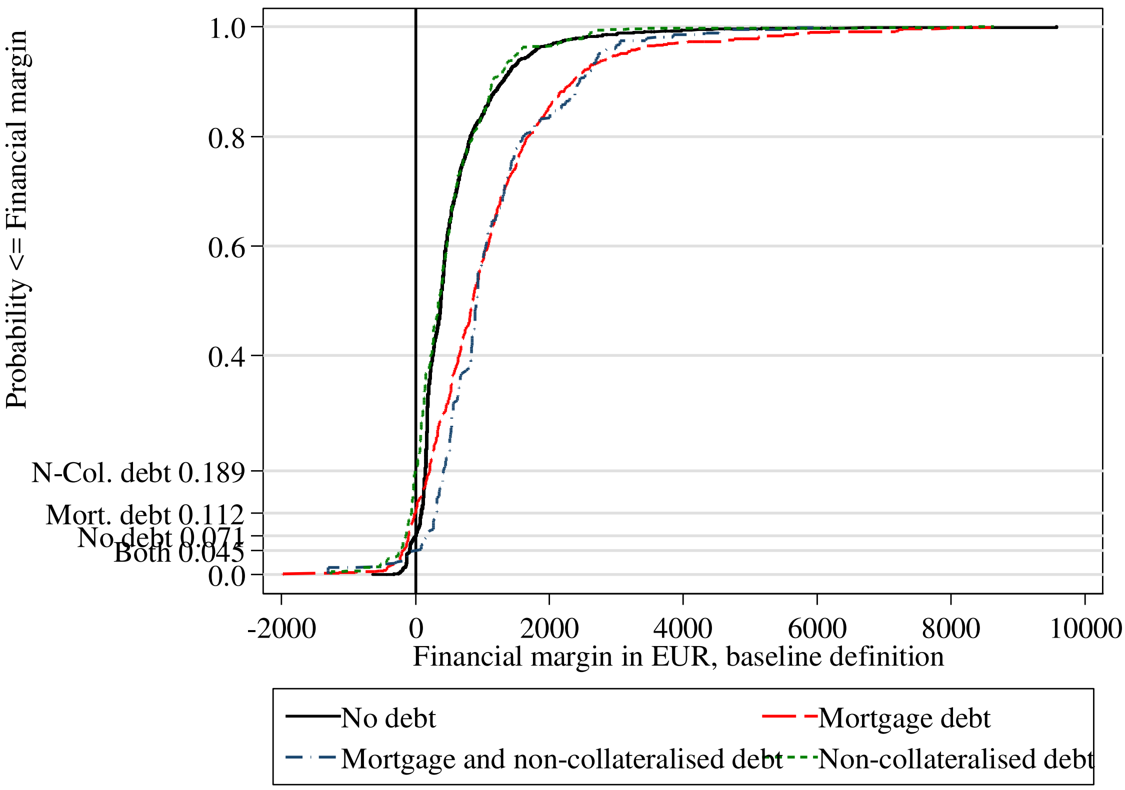

Figure 6: Distribution of the financial margin by debt participation and debt type, 2013

Note: The maximum value of the financial margin has been trimmed at 10,000 euros, which excludes five observations.

Source: Authors' calculations from the Estonian HFCS data.

Most studies of household stress tests consider all households with negative financial margin as distressed households and define their probability of default to be equal to one. However, in practice only some households with a current negative financial margin default on loans, since the probability of default is also dependent on financial buffers. Households with a substantial level of liquid assets may be able to cover the negative financial margin for some time until they manage to restore their income and so avoid default. This paper applies the solvency and liquidity approach introduced by Ampudia et al. (2016) to derive the probability of default. They show that this type of distress measure outperforms other approaches that are based on a negative financial margin or on debt service ratio thresholds, as these tend to overestimate the exposure at default.[14] It not only has a more realistic distress measure that employs information on income as well as on assets, but it also allows flexible calibration of the exposure at default ratio so that it meets the actual aggregate non-performing loan ratio. As a result, micro- and macrodata-based stress tests can easily be compared at the same meaningful scale.

Following Ampudia et al. (2016) we define the probability of default as follows:

$$\begin{gathered}
If\ FM_i \geq 0\ \ then\, pd_i = 0 \\
If\ FM_i < 0\ \wedge LIQ_i \geq |FM_i| \times M\ \ then\, pd_i = 0 \\
If\ FM_i < 0\ \wedge 0 < LIQ_i < |FM_i| \times M\ \ then\, pd_i = 1 - \frac{LIQ_i}{|FM_i|} \times \frac{1}{M} \\
If\ FM_i < 0\ \wedge LIQ_i = 0\ then\, pd_i = 1
\end{gathered} \tag{2}$$

where pd_i denotes the probability of default of household i, FM_i is the financial margin, LIQ_i are liquid assets, and M is the calibrated number of months after which the household restores its non-negative financial margin. Equation (2) assumes that M is greater than zero. Liquid assets are household net liquid assets, i.e. the sum of deposits, mutual funds, bonds, non-self-employment business wealth, publicly traded shares, and managed accounts from which bank overdraft debts and credit card debts are deducted.[15] The very first line of the set of equations (2) shows that households with a positive financial margin will not default and have a probability of default of zero. Not all the households with a negative financial margin will default; households with a negative financial margin and enough liquid assets to cover the calibrated M months of the negative financial margin will also not default. Households with a negative financial margin and no liquid assets will default with the probability of one, while households in between these two extremes will have a probability of default that is a decreasing linear function of the ratio of liquid assets to the absolute value of the financial margin.

After obtaining the estimated probabilities of default for the households, we calculate the banks' exposure at default (EAD) or the share of defaulting loans in the total loan stock. The formula for calculating EAD is (Ampudia et al. (2016):

$$EAD = \frac{\sum_{i=1}^{N} pd_i D_i}{\sum_{i=1}^{N} D_i} \tag{3}$$

where EAD denotes exposure at default and D_i is the total debt of household i. The value of M is calibrated so that the estimated EAD would meet the aggregate share of non-performing loans (NPL) in Estonia at the time of the survey, i.e. from March to June 2013. The NPL share was assessed as the percentage of household loans in the total loan stock whose payments were past due for more than 30 days, which was 3.4% during the survey fieldwork period (Bank of Estonia statistics table 3.3.11). Ampudia et al. (2016) calibrate the value of M to meet the non-performing loan ratio for the euro area households and find M to vary a lot across countries, from 0 to 26 months.[16] Given that the share of households with a negative

[14] The types of probability of default measures in stress-testing models can be divided into three groups. The first approach assesses financial fragility by finding the fraction of households whose debt-service-to-income ratio exceeds some threshold level (see e.g. Michelangeli and Pietrunti (2014), Faruqui et al. (2012), Martinez et al. (2013)). The second method is based on the share of households with a negative financial margin, assuming that all households with a negative financial margin will default (most of the papers cited in footnote 2 use this approach). The third method, which is described in this section, is used in recent studies by Ampudia et al. (2014) and Ampudia et al. (2016).

[15] These credit types are not taken into account in calculations of the financial margin.

[16] Their study covers the households of the 15 euro area countries that participated in the first wave of the HFCS survey, these being all the euro area member states in 2010 except Ireland.

financial margin in the Estonian data is high compared to the actual NPL ratio (13.0% vs 3.4%), the value of M must be relatively low in Estonia, i.e. despite the frequent negative financial margin, households can restore their financial solvency relatively quickly. The calibration shows that the calibrated value of M is one month, which results in an aggregate value of *EAD* of 3.4%.

Lastly, the share of banks' loan losses that are caused by defaults, or the loss given default (LGD), can be calculated as the probability of default multiplied by the sum of potential loan losses for mortgage loans with negative equity and the sum of all non-collateralised loans (following the idea of Herrala and Kauko (2007) and the notation of Ampudia et al. (2016b)):

$$LGD = \frac{\sum_{i=1}^{N} pd_i[(D_i^M - W_i^M)c_i^M + D_i^{NC}]}{\sum_{i=1}^{N} D_i}$$

where *LGD* denotes loss given default, *Di* denotes debt, superscript *M* denotes mortgage loans and superscript *NC* non-collateralised loans, W_i denotes assets that the bank can liquidate in the event of a default, and c_i is one if the household is "under water, meaning its collateral has a lower value than the outstanding value of its loans, while c_i is zero otherwise. The value of W_i is taken as the value of all the real estate assets that a given household owns. The *LGD* provides an estimate of the potential losses for banks from non-performing loans.

Table 1 reports descriptive statistics for the financial fragility indicators: the share of households with a negative financial margin, the probability of default, etc. The first column presents estimates based on the aggregate historic banking sector data from the survey period, i.e. the second quarter of 2013. The aggregate non-performing loan rate is based on loan payments past due more than 30 days and is obtained from the Bank of Estonia statistics table 3.3.11. As discussed above, we have calibrated our model so that the microdata-based exposure at default rate meets this non-performing loan rate. The microdata-based loss given default rate is benchmarked against the aggregate loan loss provision rate. These data come from the Bank of Estonia credit risk model. The aggregate provision rates are much higher than predicted by the microdata, and there are two possible reasons for that. First, provisions can also cover restructured loans and second, the models used by commercial banks for provisioning may be more conservative than our definition of loss given default.[17] This implies that banks proceed from the estimate of the ready sale price of the real estate, which might be only 75% or 80% of the market value. Our definition of loss given default in the microdata is less conservative and is based on the market value of the real estate. However, only small numbers of loans have been written off even in the aftermath of the Great Recession in Estonia, which suggests that banks have historically often been overprovisioning. See Figure A1 in Appendix 4 for the developments in the aggregate non-performing loan rate, the loan loss provision rate and the write-off rate in the household and corporate sectors.

The second column of Table 1 gives the indicators that are derived using the baseline definitions in the current subsection and estimated using the HFCS data for Estonia. The share of households with a negative financial margin is 13.0%, which is similar in magnitude to the euro area figure of 12.3% (Ampudia et al. (2016)).[18] This share of households with a negative financial margin corresponds to an average probability of default of 5.2% and exposure at default of 3.4%. That exposure at default is lower than the probability of default shows that

[17] We are grateful to our colleagues from the Bank of Estonia financial stability department for these insights into the aggregate loan loss provision rate in Estonia.

[18] The percentage of households with a negative financial margin for the euro area is calculated using the HFCS first wave results and with basic consumption defined as 20% of the median income.

households with a high probability of default have smaller debt stocks. This is in correspondence with the findings from Figure 6, which indicate that households with non-collateralised loans are usually financially more fragile. The value of loans exposed to default is 165.9 million euros and this corresponds to a value for loss given default of 20.6 million euros. The number of indebted households in the survey is 769, which corresponds to a share of indebted households of 30.5%. This share is somewhat lower than the share reported in the descriptive report of the survey (Meriküll and Rõõm (2016)) because credit card debt and credit line overdraft debt have been excluded from the calculations of the financial margin as the debt servicing costs of these credit types have not been collected by the survey.

It is surprising that although a relatively large number of households have a negative financial margin in Estonia, few of them have such problems paying back their debt that they enter into default. The analysis in Section 3 showed that the financial buffers of Estonian households are low, so they must have access to other sources of money to service their debt when they face economic difficulties. Possible sources of additional liquidity are access to short-term credit or financial help from relatives and friends. The data point to the importance of social networks in overcoming economic difficulties in Estonia, as 45% of households would get help from relatives or friends if they encountered economic difficulties, which is about twice the euro area average of 22%. As many as 62% of households could get 1000 EUR of help from friends and relatives outside the household and 23% of households could get help worth 5000 EUR. Using credit to overcome financial difficulties is less common in Estonia than in the rest of the euro area, as 10% of households in Estonia would get a credit card and 5% would get other loans if they faced economic difficulties, while the respective numbers in the euro area are 23% and 15%. The availability of financial help from friends and relatives for overcoming economic difficulties is equally important for Estonian households with debt and for those without.

4.2. Alternative measures for the household probability of default

This subsection tests the robustness of the baseline definition of financial fragility using alternative measures of the financial margin and the corresponding probability of default taken from the survey and from administrative sources. Four alternative definitions are drawn from the survey data. First, households' self-reported expenditure on food and utilities is used as a proxy for essential consumption. These consumption categories cover expenditure on food consumption at home and outside the home and on utilities such as heating, electricity and water. Second, the total expenditure on non-durable goods is used as a proxy for essential consumption. This consumption category covers the consumption items already listed plus expenditure on other non-durable goods such as clothes, transport and recreation. The reference period for the consumption data is expenditure in a typical month. These two proxies for essential consumption have been used to calculate the alternative measures of the financial margin.

The third alternative definition of financial fragility uses self-reported information from households on whether they had debt repayment problems during the 12 months before the survey. If a household had problems in paying back debt, its probability of default is taken to be one and if it did not have any such problems its probability of default is taken to be zero. The probability of default calculated on the basis of this approach is very high, since as many as 17.2% of the households had had debt repayment problems in the preceding 12 months. This share is similar in magnitude to that found in a recent study on Estonian microdata by

Merike Kukk (2016). She finds that around 13% of households had some debt repayment problems in the period from 2004 to 2012 in Estonia.

The fourth alternative indicator of financial fragility is defined using self-reported information from households on whether their expenditure exceeded their income during the last 12 months. If they had such problems, an additional question was asked to indicate how much the expenditure exceeded income by, and this information is used to calculate an alternative measure of the financial margin.

The estimated probability of default, the EAD and the LGD found using these alternative definitions are reported in Table 1, columns (3) to (6). The value of 1 month for *M*, the same as in the baseline definition, is applied for the alternative definitions of financial fragility. The estimated probabilities of default found using the alternative measures of the financial margin are higher than that for the baseline estimation and this difference is the strongest for the second and third alternative measures (columns (4) and (5) in Table 1). The estimated EADs that are based on alternative definitions of the financial margin are higher than the aggregate share of NPLs. The only alternative specification that gives similar results to the baseline is the one based on self-reported information from households on whether their expenditures exceeded income (column (6)).

We also compare the baseline probability of default against the estimates based on data from administrative sources. The components of household balance sheet and income have been replaced one by one by the corresponding estimates from administrative sources to understand what effect their separate replacement has on financial fragility indicators. Table 2 presents the results. Column (2) reports the results where the survey-based household income is replaced by administrative income data. The household incomes derived from administrative sources tend to be lower than those based on the survey. A possible reason for this difference is that the survey also covers non-reported income, at least in part. Alternatively, the difference may be caused by measurement error (income overreporting by survey participants). Lower estimated income from administrative sources raises the share of households with a negative financial margin, and results in a higher exposure at default rate and substantially larger losses for the banks.

The third column of Table 2 reports the results when survey-based measures of debt servicing costs and the outstanding balance of loans are replaced by measures based on the data from administrative sources. The first outcome from this replacement is that the share of indebted households increases to 37.1%, indicating that the share of debt participation is underestimated by the survey. Further analysis by debt components shows that the HMR mortgages are accurately predicted, while other real estate loans and consumer loans are under-represented in the survey. One possible explanation for this tendency is respondent fatigue as the data on household main residence mortgages are collected first, then the other real estate collateralised mortgages and then consumer loans. An alternative possibility is response bias, as households may systematically under-report non-collateralised loans. Replacing debt items from administrative sources adds households with relatively smaller loans and loan servicing costs to the group of indebted households and the share of households with a negative financial margin decreases. However, as the total amount of loans covered increases, the exposure at default and loss given default increase relative to the results with the baseline measures.

Table 1: Indicators of the financial fragility of households and estimated loan losses for banks

	(1) Aggregate historic measures [a)]	(2) Baseline definition: C = subsistence minimum	(3) C = food and utilities	(4) C = food, utilities and other non-durables	(5) Debt repayment problems in the last 12 months	(6) Expenses exceeded income in the last 12 months [b)]
Negative financial margin, %	.	13.0	24.8	37.4	.	16.0
Probability of default, %	.	5.2	10.8	15.8	17.2	7.8
Exposure at default, %	3.4	3.4	8.2	11.3	11.9	4.8
...mortgages, %	2.8	3.2	8.0	11.0	11.4	4.8
...non-collateralised loans, %	6.4	8.8	13.7	18.7	22.5	4.6
Exposure at default, mln EUR	230.7	165.9	400.1	552.6	578.2	231.2
...mortgages, mln EUR	163.0	147.4	371.4	513.5	531.2	221.7
...non-collateralised loans, mln EUR	67.2	18.5	28.6	39.1	47.0	9.5
Loss given default, %	0.8	0.4	0.7	1.0	1.6	0.4
...mortgages, %	0.5	0.0	0.1	0.2	0.6	0.2
...non-collateralised loans, %	2.5	8.8	13.7	18.7	22.5	4.6
Loss given default, ml EUR	55.5	20.6	31.9	47.6	77.1	20.4
...mortgages, mln EUR	29.8	2.1	3.2	8.5	30.1	10.9
...non-collateralised loans, mln EUR	25.8	18.5	28.6	39.1	47.0	9.5
No of obs.	.	769	769	769	769	760

Source: Authors' calculations from Estonian HFCS data; the Bank of Estonia statistics table 3.3.11 for the aggregate non-performing loans; and the Bank of Estonia credit risk model for loan loss provisions.

Notes: Indebted households are defined as households with collateralised debt and with consumer loans, not including leases, credit line overdraft and credit card debt.

[a)] Exposure at default is measured as the aggregate ratio of non-performing loans with debt payments 30 days or more past due in the survey period. Loss given default is measured using the aggregate loan loss provisions of the commercial banks.

[b)] If a household responded that expenses exceeded income, an additional question was asked about how much larger than income the expenses were. This question has been used to estimate the size of the negative financial margin. Around 10% of households did not report the size of their negative financial margin and these cases had to be excluded from the calculations of this column.

Table 2: Indicators of the financial fragility of households and potential losses for banks, estimations based on administrative sources

	(1) Baseline from the survey	(2) Replacing income from administrative sources	(3) Replacing debt from administrative sources	(4) Replacing assets from administrative sources	(5) All components from administrative sources
Negative financial margin, %	13.0	17.0	10.5	13.0	15.6
Probability of default, %	5.2	6.8	3.6	5.0	6.4
Exposure at default, %	3.4	3.8	3.8	3.4	5.8
...mortgages, %	3.2	3.5	4.0	3.1	5.9
...non-collateralised loans, %	8.8	12.0	1.5	9.2	5.0
Exposure at default, mln EUR	165.9	186.1	220.6	164.3	336.2
...mortgages, mln EUR	147.4	161.0	212.8	145.1	310.6
...non-collateralised loans, mln EUR	18.5	25.1	7.8	19.3	25.6
Loss given default, %	0.4	0.8	0.5	1.5	1.1
...mortgages, %	0.0	0.3	0.4	1.1	0.7
...non-collateralised loans, %	8.8	12.0	1.5	9.2	5.0
Loss given default, mln EUR	20.6	39.5	28.5	71.4	61.5
...mortgages, mln EUR	2.1	14.4	20.6	52.2	35.9
...non-collateralised loans, mln EUR	18.5	25.1	7.8	19.3	25.6
No of obs.	769	769	944	769	944

Source: Authors' calculations from Estonian HFCS survey and administrative data.
Notes: Indebted households are defined as households with collateralised debt and with consumer loans, not including leases, credit line overdraft and credit card debt.

Lastly, we replace the values of all real assets and liquid financial assets with data from the administrative sources. The probability of default declines slightly from this replacement, indicating that liquid assets are somewhat under-reported by the survey. The estimated loss given default more than triples as a result of this replacement, which shows that the value of real assets found from the data from administrative sources tends to be smaller than the survey-based values. The real estate prices from administrative sources are based on regional transaction prices in the survey period. They may overestimate or underestimate the value of the real estate in the region because of possible composition bias. Even so, the difference between the survey values and the administrative values is quite substantial, which indicates a possible overestimation of the real estate values based on the self-assessments by households in the survey.

The fifth column of Table 2 replaces all the components of the financial margin with measures derived using the data from administrative sources. These measures find a somewhat higher rate for the probability of default than the survey-based estimates do, together with substantially higher losses for the banks, especially from mortgage loans. The values for loss given default found from data from administrative sources are much closer to the aggregate loan loss provisions reported in the first column of Table 1 than to the survey-based measures.

Another relevant aspect of robustness is whether all these alternative measures of the probability of default point to the same set of financially fragile households. For that purpose we calculated the correlations between the alternative definitions of the probability of default. These correlation coefficients are presented in Table A4 in Appendix 5. The probabilities of default are well correlated for the first three survey based indicators as the coefficients indicate strong correlation from 0.5 to 0.8. This is an expected result since only one component of the financial margin, consumption, varies across these definitions. The correlations are weaker with the other survey-based definitions of the probability of default, with the correlation coefficients varying from 0.2 to 0.4. The correlation coefficient between the baseline measure of the probability of default based on survey data and the same indicator based on the administrative data is 0.3.

4.3. Which households are more likely to default on loans?

We use multivariate analysis to estimate which household characteristics were significantly associated with the probability of default. The estimation results, which are based on regressions on five alternative measures of the probability of default, are presented in Table A5 in Appendix 6.

First, contrary to our expectations, the type of debt that a household has is not significantly related to the probability of default. Our prior assumption was that non-collateralised loans are more likely to default, but the regression results did not confirm this perception. In addition, the number of loans a household has is not correlated with the probability of default.

Household income is strongly negatively related with the probability of default. The coefficient estimates are significantly negative and decreasing across income groups for the first four measures of the probability of default. The relationship with income is the weakest for the last alternative measure, which is based on the direct answers by households about whether their expenses exceeded income during the last 12 months. For the last measure the estimated coefficient is significant at the 10% level only for the highest income quintile. The result that low-income households are strongly more likely to default on their loans corresponds with the findings indicating that indebted households in the first income quintile also have the highest leverage relative to their income (see the regression estimates in Table A2 in Appendix 2).

There is no significant relationship between the probability of default and the level of net wealth. The association with the age of the household reference person is also relatively weak. The estimated coefficients are significantly positive for the first measure of the probability of default for households where the reference person's age is between 45 and 64. According to the third measure, younger households are more likely to default. For other alternative measures the estimated coefficients for age groups are mainly insignificant. In addition, households where the reference person is retired are less likely to default, the estimated coefficients being significantly negative for three measures of default.

Perhaps the most interesting finding from these regressions is that the education level of the household reference person is related to the probability of default. This result is noteworthy, since education still has additional explanatory power even after income and wealth have been controlled for. We find that households where the reference person has tertiary education have a significantly lower probability of default than households where the reference person has only a primary level of education. The coefficients are significant for four alternative measures out of five. The regression estimates are also negative for secondary education (compared to primary) but in this case the relationship is weaker as only two coefficients out of five alternatives are significant. The negative relationship between the probability of default on loans and the education level indicates that formal education is correlated with financial literacy and it highlights the importance of financial literacy in prudent household financial decisions.

5. Household stress tests: the impact of shocks on financial fragility

This section gives the results of stress tests, presenting first the results of standardised individual shocks and then the results of a simultaneous shock mimicking the changes in the aggregate variables during the Great Recession in Estonia. The standardised shocks are defined as shocks of one, two and three standard deviations in the base interest rate, unemployment and real estate prices. The standard deviation is calculated on the basis of the quarterly data covering the period 2004q1–2013q2[19] (i.e. the period from the EU accession until the time of the survey fieldwork). The dynamics of GDP and the shocked macro variables are presented in Appendix 7, Figure A2. It is assumed that shocks occur instantaneously and that there is no feedback from the financial sector to the real economy.

5.1. The effect of individual shocks on financial fragility

5.1.1. The interest rate shock

The base interest rate shock is assumed to affect only mortgage loan payments with adjustable interest rates, while mortgage loan payments with fixed interest rates and non-collateralised loan payments are assumed to remain unaffected by this shock.[20] Mortgage loan payments with adjustable interest rates have two parts, the principal and the interest payments. The payments of the principal are unaffected by the shock, while the interest payments rise because of the higher base rate. The share of adjustable interest rate mortgages is 82% of the total mortgage stock in Estonia (authors' calculations from the Estonian HFCS). This puts Estonia together with Luxembourg, Malta, the Netherlands, Portugal, Slovenia and Spain in

[19] The earlier years were excluded as these were seriously affected by structural changes caused by the transition from a planned to a market economy. The market for mortgage loans was practically non-existent in the 1990s and interest rates and the unemployment rate were substantially higher before EU accession than after it. See more discussion about housing and mortgage market developments in this period in Meriküll and Rõõm (2016).

[20] It is also assumed that the Euribor shock will affect the income earned from sight and savings accounts. However, the income from these sources is so small compared to other income sources that it has almost no effect on the financial margin of households.

the group of countries with the highest share of adjustable rate loans in the euro area (see Ampudia et al. (2014) for the other euro area countries). Consequently, the pass-through of this shock to the financial margin is relatively strong in Estonia.

The HFCS does not collect information on whether non-collateralised loans have flexible or adjustable interest rates, but it is known that most of these loans have fixed interest rates in Estonia.[21] This supports our assumption of zero pass-through of the base interest rate shock to non-collateralised loans.

The most common base interest rate in Estonia is the six-month Euribor. As much as 95% of all mortgage loans with adjustable interest rates are tied to this base rate (authors' calculations from the Estonian HFCS). The rest of the loans are tied to the Euribor rates with other durations or to the commercial banks' own base rates. As the other base rates also follow the dynamics of the six-month Euribor rate, all the adjustable interest rate mortgages are assumed to be affected by the shock to this variable.

The six-month Euribor was 0.318% at the time of the survey and its standard deviation for the post-EU-accession period was 1.413%. This means that shocks of one, two and three standard deviations correspond to an increase in the Euribor from 0.318% to 1.1731%, 3.144% and 4.557%. Although a shock as large as three standard deviations should capture extreme developments, the highest shocked value of 4.557% is still 0.5 pp smaller than the highest value seen in the sample period, which was 5.176% in the second quarter of 2008 (see Appendix 7). This indicates that the variation in the Euribor rate has been quite low.

The results of the Euribor shock are presented in Table 3. Shocks of one, two and three standard deviations increase the share of households with a negative financial margin almost linearly, while the probability of default and exposure at default react more strongly to smaller shocks. This indicates that households with a higher negative financial margin in its absolute value have more liquid assets and they can overcome financial difficulties without a strong increase in the probability of default. The exposure at default reacts quite strongly to this shock, as a one standard deviation increase in the Euribor increases the exposure at default rate from 3.4% to 4.9%, which corresponds to a 44% increase. However, despite the substantial increase in loans exposed to default, the potential losses from these loans are minimal. Most of the total loss is caused by non-collateralised loans, which are not affected by the interest rate shock, while the increase in losses from mortgages is not sensitive to smaller shocks in the base interest rate.

[21] As much as 67% of the consumer loan stock issued by banks had fixed interest rates in the second quarter of 2013. These loans included leases for cars, which usually have adjustable interest rates and are not covered by the HFCS (Bank of Estonia internal statistics from the Financial Stability Department). So the actual share of fixed interest rate loans among non-collateralised debt is even higher in the HFCS data.

Table 3: The effect of a shock to the Euribor interest rate on the financial fragility of households

	Pre-stress, Euribor = 0.318%	1 sd shock, Euribor = 1.731%	2 sd shock, Euribor = 3.144%	3 sd shock, Euribor = 4.557%
Negative financial margin, %	13.0	13.8	14.6	15.3
Probability of default, %	5.2	5.9	6.1	6.4
Exposure at default, %	3.4	4.9	5.3	5.9
...mortgages, %	3.2	4.8	5.1	5.8
...non-collateralised loans, %	8.8	8.8	8.8	8.8
Exposure at default, mln EUR	165.9	240.6	258.3	289.7
...mortgages, mln EUR	147.4	222.2	239.8	271.2
...non-collateralised loans, mln EUR	18.5	18.5	18.5	18.5
Loss given default, %	0.4	0.4	0.4	0.4
...mortgages, %	0.0	0.0	0.0	0.1
...non-collateralised loans, %	8.8	8.8	8.8	8.8
Loss given default, mln EUR	20.6	20.6	20.6	21.1
...mortgages, mln EUR	2.1	2.1	2.1	2.6
...non-collateralised loans, mln EUR	18.5	18.5	18.5	18.5
No of obs.	769.0	769.0	769.0	769.0

Note: sd stands for standard deviation.
Source: Authors' calculations from Estonian HFCS data.

5.1.2. The unemployment shock

There are various ways to estimate the impact of an unemployment shock on the household financial margin. The simplest approaches assume equal unemployment risk across individuals (Johansson and Persson (2006), Herrala and Kaukko (2007)), while more advanced approaches assume idiosyncratic shocks to unemployment probability, taking into account that individuals with different personal characteristics such as age, gender and education have a different propensity for becoming unemployed (Albacete and Fessler (2010), Bilston et al. (2015), Galuščák et al. (2016), Ampudia et al. (2014b), and Bańbuła et al. (2015)). The last three of the cited papers take a step further and also model transitions from unemployment to employment on top of the probability of becoming unemployed.

Given our focus on the effects of adverse shocks, only the increase in the inflow from employment to unemployment is modelled in this paper. It is assumed that individuals who are unemployed at the time of the survey stay in unemployment after the shock. In addition, some individuals move from employment to unemployment, so that the increase in the unemployment rate meets the size of the shock. It is also assumed that the share of economically inactive people is unaffected by the shock. So our modelling of the unemployment shock assumes that the new and higher unemployment rate is caused by the change in one labour market flow, i.e. the flow from employment to unemployment, while other labour market flows remain unaltered.

These assumptions follow the logic of any labour market in recession where first hiring is cut and then separation increases because of adverse shocks (Davis and Haltiwanger (1999)). The assumptions are also in line with the developments in the Estonian labour market during the Great Recession (see e.g. Meriküll (2016)). The unemployment rate mainly increased because of the high separation rate, while the hiring rate was very low throughout the crisis years. Despite the sluggish recovery of employment, job-seekers did not switch from unemployment to inactivity and the activity rate remained relatively stable over the boom, bust and recovery.

The simulation of the unemployment shock is estimated using the approach taken by Albacete and Fessler (2010). Unlike in their analysis, unemployment is assessed at the individual and not at the household level and currently unemployed individuals are assumed to stay in unemployment in this paper. The shock is calculated in three steps. First, the predicted probability of each individual being unemployed is calculated using the logit model. Conventional regressors for the unemployment equation are used, such as gender, age, marriage, ethnicity, education and region.[22]

Second, the constant term in the unemployment equation is manipulated to meet the new aggregate shock value of unemployment. Third, a random probability is drawn for each individual from a uniform distribution between zero and one. The model-based predicted probability of unemployment is compared to the random probability for each employed individual and if the predicted probability is larger than the random value, a switch from employment to unemployment is assigned for that person. Individuals who become unemployed are assigned new reduced gross incomes, which are equal to the previous gross wage income times the average replacement rate of 15%. The average replacement rate has been calculated using the crisis years of 2009 and 2010, which are taken as a good predictor of the replacement rate under a negative labour demand shock.[23] The new household-level disposable i-come and financial margin are derived and the new values of the aggregate financial fragility indicators are calculated. This procedure is repeated 1000 times using a Monte Carlo simulation and the effect of the unemployment shock is found as the average value of financial fragility indicators from these 1000 replications.

The unemployment rate is 10.9% in the HFCS data, which is somewhat higher than the official estimates from the Labour Force Survey, which were 10.0% and 8.0% in the first and the second quarters of 2013. The standard deviation of the official seasonally adjusted rate is 3.9%, which shows quite high variation for this variable. For example, the shock of three standard deviations would increase the sample unemployment rate to 22.8%, which is higher than the historical quarterly maximum since 2004, which was 18.8% (see Appendix 7).

The results of the unemployment shock are presented in Table 4. The share of households with a negative financial margin increases more strongly than it did in response to the interest

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[22] The marginal effects of the model are reported in Appendix 8. Men, unmarried individuals, people of non-Estonian ethnicity, those with lower education and those from Ida-Viru county have a higher probability of being unemployed.

[23] All workers who are involuntarily separated from work due to job destruction are subject to unemployment insurance in Estonia. The insurance benefit is 50% of the previous wage for the first three months and 40% for up to the next nine months dependent on the previous employment tenure. However, not all workers are eligible for the unemployment insurance. According to the labour force survey, roughly 70% of workers who have moved from employment to unemployment within a year are registered with the Unemployment Office and of these only 50% receive unemployment insurance, while 25% receive unemployment benefit and 25% do not receive any transfers. These regularities held during the crisis years of 2009 and 2010, when most of the separations were due to job destruction. Given that we do not have enough detailed information on employment tenure and that not all the workers are eligible to receive unemployment insurance, we used as a replacement rate the average replacement rate of the crisis years from the Labour Force Survey. The income of an unemployed person is assumed to consist of an unemployment insurance payment, unemployment benefit and a training scholarship from the Unemployment Office. The severance payment is not covered by the Labour Force survey. The size of the severance payment can be up to two months' salary.

rate shock. This shows that a wider set of households are affected by the unemployment shock. However, the exposure at default is affected less strongly than in response to the interest rate shock, which indicates that the households affected by the unemployment shock usually have smaller loans than the households affected by the interest rate shock. The loan payments on non-collateralised loans are not affected by the interest rate shock and the outstanding amounts of non-collateralised loans are smaller than mortgage loans, but the exposure at default of mortgage loans is affected less by the unemployment shock. At the same time, the potential losses for the banks from the unemployment shock are larger than those from the interest rate shock. This originates from non-collateralised loans and also from mortgage loans. Evidently, households that are more strongly affected by the unemployment shock have higher loan-to-value ratios than households which are affected more by the interest rate shock.

Table 4: The effect of the unemployment shock on the financial fragility of households

	Pre-stress, unemployment rate = 10.9%	1 sd shock, unemployment rate =14.8%	2 sd shock, unemployment rate =18.8%	3 sd shock, unemployment rate = 22.8%
Negative financial margin, %	13.0	14.3	15.7	17.1
Probability of default, %	5.2	5.8	6.5	7.1
Exposure at default, %	3.4	3.8	4.3	4.8
...mortgages, %	3.2	3.6	4.1	4.5
...non-collateralised loans, %	8.8	9.4	9.9	10.5
Exposure at default, mln EUR	165.9	186.0	210.3	232.9
...mortgages, mln EUR	147.4	166.4	189.5	211.0
...non-collateralised loans, mln EUR	18.5	19.6	20.8	21.9
Loss given default, %	0.4	0.5	0.5	0.6
...mortgages, %	0.0	0.1	0.1	0.1
...non-collateralised loans, %	8.8	9.4	9.9	10.5
Loss given default, mln EUR	20.6	22.7	25.1	27.2
...mortgages, mln EUR	2.1	3.1	4.3	5.4
...non-collateralised loans, mln EUR	18.5	19.6	20.8	21.9
No of obs	769.0	769.0	769.0	769.0

Note: sd stands for standard deviation.
Source: Authors' calculations from the Estonian HFCS data.

5.1.3. The real estate price shock

The real estate price shock does not affect the financial margin of households since it is calculated using flow variables related to income and expenditures and does not depend on the value of assets. This means that the probability of default and exposure at default do not depend on the real estate price shock either and this shock affects only loss given default. A fall in real estate prices increases loan-to-value ratios and the number of households with negative equity.

The average loan-to-value ratio of the household main residence is higher in Estonia than in the euro area (see Figure 4). There are two main reasons for this: first, the mortgage stock was accumulated relatively recently and second, Estonia experienced a boom and bust cycle in house prices which culminated during the Great Recession, and real estate prices at the time of the survey had not yet recovered to their pre-crisis level (Meriküll and Rõõm (2016)). House prices dropped by 50% between 2007 and 2009 in Estonia, and while this was followed by a recovery in the real estate market, house prices were still only at 70% of their highest historical value at the time of the survey (see Appendix 7). All this implies that Estonian households are expected to be more vulnerable to a real estate price shock than the euro area households are on average.

The volatile development of real estate prices is reflected in the high standard deviation in this variable. One standard deviation in the real estate price index corresponds to a change of 24.4% in prices. This is much higher than in other euro area countries and even substantially higher than in the country with the highest standard deviation in the study by Ampudia et al. (2016), Spain, where it was 14.3%. Given the sizeable standard deviation in Estonia, a shock of three standard deviations cannot be considered realistic. The two standard deviation shock of 48.8% corresponds to the decline in real estate prices during the Great Recession.

The results of the real estate price shock are presented in Table 5. Although it is only the losses from mortgage loans that are affected by this shock, it has a strong adverse effect on loan losses. Even a shock of only one standard deviation causes the losses from mortgages to increase six times over. There is also a strong non-linearity in this reaction, as the shock of two standard deviations triples the losses of the one standard deviation shock and the shock of three standard deviations doubles the losses from the two standard deviation shock. The take-away from this non-linearity is that the bulk of households with a negative financial margin have high loan-to-value ratios and the deterioration in real estate prices drives them quickly into negative equity.

Table 5: The effect of the shock to real estate prices on the financial fragility of households

	Pre-stress	1 sd shock, decrease = 24.4%	2 sd shock, decrease = 48.8%	3 sd shock, decrease = 73.2%
Negative financial margin, %	13.0	13.0	13.0	13.0
Probability of default, %	5.2	5.2	5.2	5.2
Exposure at default, %	3.4	3.4	3.4	3.4
...mortgages, %	3.2	3.2	3.2	3.2
...non-collateralised loans, %	8.8	8.8	8.8	8.8
Exposure at default, mln EUR	165.9	165.9	165.9	165.9
...mortgages, mln EUR	147.4	147.4	147.4	147.4
...non-collateralised loans, mln EUR	18.5	18.5	18.5	18.5
Loss given default, %	0.4	0.6	1.1	1.9
...mortgages, %	0.0	0.3	0.8	1.6
...non-collateralised loans, %	8.8	8.8	8.8	8.8
Loss given default, mln EUR	20.6	31.0	55.3	91.6
...mortgages, mln EUR	2.1	12.6	36.8	73.1
...non-collateralised loans, mln EUR	18.5	18.5	18.5	18.5
No of obs	769.0	769.0	769.0	769.0

Note: sd stands for standard deviation.
Source: Authors' calculations from Estonian HFCS data.

5.1.4. The impact of standardised shocks across households with different characteristics

The previous subsections describing the impact of various shocks on the financial fragility of households showed the aggregate reaction to the deterioration in each shocked variable, but the discussion of aggregate reaction did not say much about the heterogeneous reaction of households. This subsection will review which households are more vulnerable to shocks and which households are responsible for most of the loan losses that occur because of the shocks. The households are grouped by four characteristics: net income, net wealth, age of the household reference person[24] and household size.

The financial vulnerability of households is best captured by the probability of default. Figure 7 shows the variation in the average value of the probability of default across the household characteristics listed above and for four scenarios: pre-stress, one standard deviation interest rate shock, one standard deviation unemployment shock, and one standard deviation real estate price shock. The figure repeats the message from the multivariate analysis in the previous section, namely that financial vulnerability is highest for low income households, but is also high for small households, low net wealth households and households with middle-aged reference people. The variation in the probability of default is strongest across income groups, ranging from 40% for the lowest quintile to near-zero values for the upper three quintiles.

The effects of one standard deviation shocks on the rates for the probability of default are limited. The strongest effects are caused by the interest rate shock, followed by the unemployment shock. The real estate price shock has no impact on the probability of default, since it does not affect the flow variables (income and expenditures) that drive the probability. Figure 7 implies that the impact of the interest rate and unemployment rate shocks is the strongest for households from the second and third income quintiles and with young or middle-aged reference persons, with low levels of net wealth and with only one member. It is also visible that the unemployment shock affects households more equally, while the effect of the interest rate shock is clearly concentrated to households in the 45 to 54 age group.

The differences in the impact of shocks across household characteristics are more pronounced in the monetary value of exposure at default, which is a better characterisation of the risks for lenders, as a high probability of default does not imply high risks for the financial sector if the amounts of debt involved are small. Figures 8 and 9 present exposure at default and loss given default in thousands of euros. As already discussed, exposure at default is affected most by the interest rate shock. Figure 8 shows that in addition to the strong reaction in exposure, the impact of this shock is also highly concentrated. The interest rate shock has the strongest impact on households from the second and third income quintiles, from the 45–54 age group, from single-member households and from the two lowest net wealth quintiles.

Loss given default is more concentrated in specific household groups than exposure at default. Households from the lowest income quintile, from the lowest net wealth quintile, from the 45–54 age group, and single person households are responsible for the majority of losses. The real estate price shock leads to the largest losses for the banking sector compared to the other standardised shocks and the impact of this shock is the strongest for households in the lowest income and net wealth quintiles.

[24] The household reference person is defined following the Canberra definition (UNECE (2011)). See Meriküll and Rõõm (2016) for a description of its derivation.

The results of the standardised shocks show that unlike other Central and Eastern European countries (see Galuščák et al. (2016) and Hóllo and Papp (2007)) and despite the low replacement rate, the unemployment shock does not have the most harmful effect on the probability of households defaulting and on banking sector losses. The interest rate shock has a relatively strong impact in Estonia on the probability of households defaulting, which is similar to findings for Nordic and Central European countries (Johanssson and Persson (2006), Herrala and Kauko (2007) and Albacete and Fessler (2010)). However, the most harmful shock for financial stability is the decline in real estate prices, which leads to the largest losses for the banks. This is related to the fast and substantial debt accumulation of Estonian households and the historically volatile real estate prices, so that the loan-to-value ratios of mortgage loans are high and the simulated shocks of one, two and three standard deviations have a strong impact on the value of real estate assets.

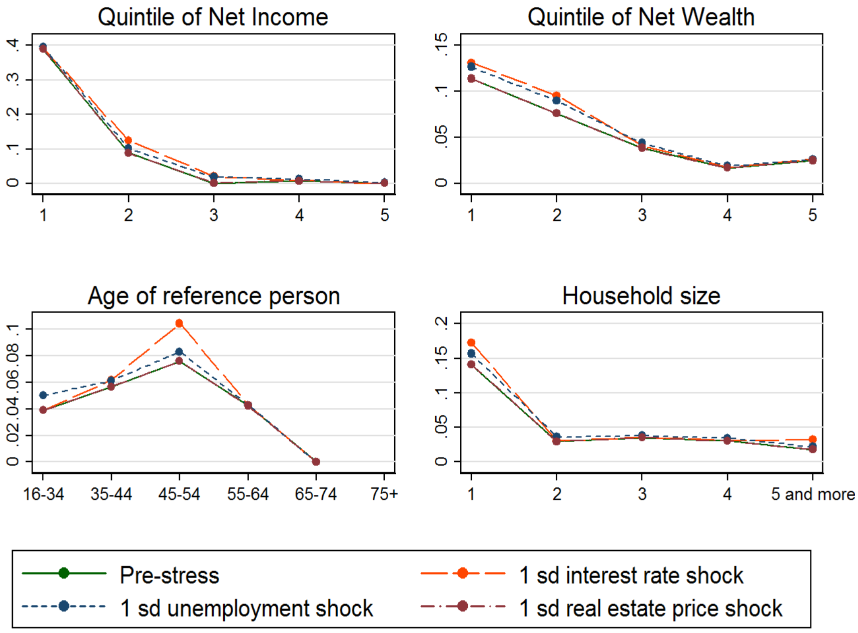

Figure 7: Variation in the probability of default (%) across households with different characteristics and in response to different shocks

Note: sd stands for standard deviation. The value for households in the 75+ age group is not reported as there were fewer than 20 such indebted households in the sample.
Source: Authors' calculations from the Estonian HFCS data.

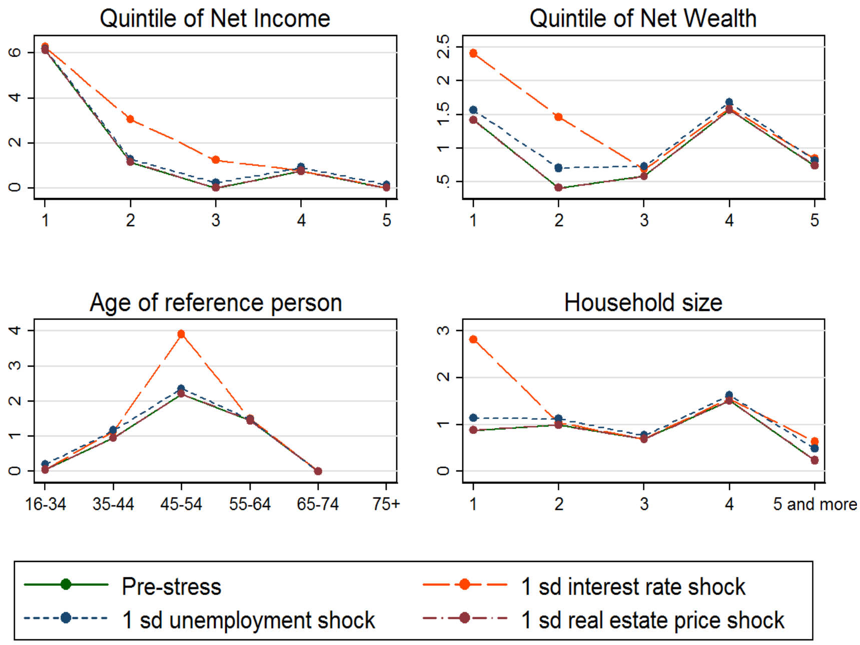

Figure 8: Variation in exposure at default across households with different characteristics and in response to different shocks, in thousands of EUR per household

Note: sd stands for standard deviation. The value for households in the 75+ age group is not reported as there were fewer than 20 such indebted households in the sample.
Source: Authors' calculations from the Estonian HFCS data.

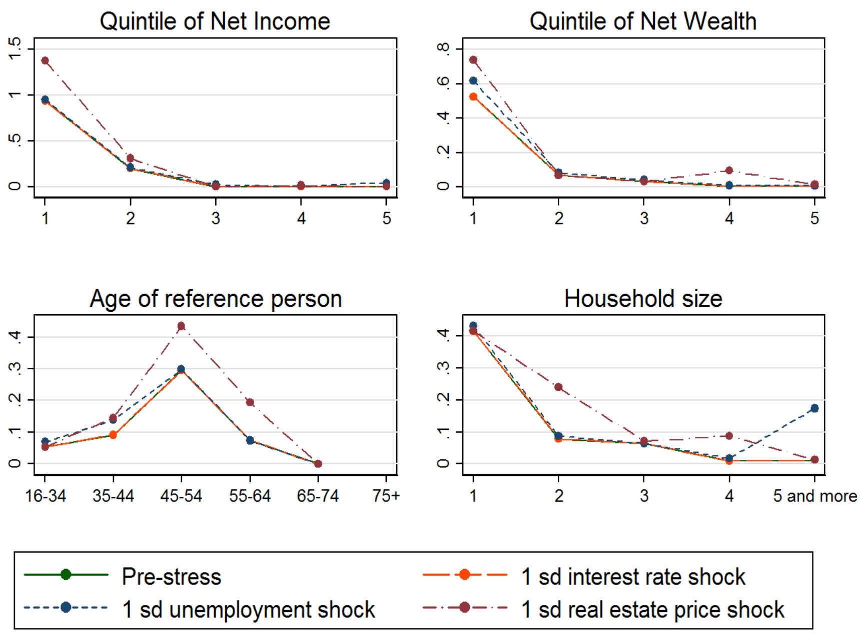

Figure 9: Variation in loss given default across households with different characteristics and in response to different shocks, in thousands of EUR per household

Note: sd stands for standard deviation. The value for households in the 75+ age group is not reported as there were fewer than 20 such indebted households in the sample.
Source: Authors' calculations from the Estonian HFCS data.

5.2. The effect of the simulated dynamics of the shocked variables on financial fragility

This subsection studies the effect of simultaneous shocks in all the three variables considered in the previous section, mimicking the aggregate movements in these variables during the Great Recession. The economic decline in Estonia in 2008–2009 was one of the most severe in any of the European countries. GDP dropped by 14% in 2009 and a decrease of this magnitude is very rare for non-war times (see Appendix 7 Figure A2 for the dynamics of macro variables). The decline was caused by a combination of negative demand shocks in domestic and foreign markets, and a sudden stop in the previously generous supply of credit from foreign-owned banks.[25] It is unlikely that a similarly severe shock would hit the Estonian economy again in the near future, because the severity of the crisis was to a large extent caused by the adjustment of the imbalances in the economy that arose in the boom period. However, the Great Recession provides an interesting example of an extreme scenario that it is proven can actually happen.

The dynamics of the shocked variables during the Great Recession are depicted in Figure A2 in Appendix 7. There were different lag periods in the reaction to the crisis for these variables, as housing prices reacted first to the decline in GDP while the reaction in unemployment was much more sluggish. The Euribor rate increased in the first phase of the crisis and started declining from the second half of 2008 as the central banks in the euro area reacted to the crisis. The uncorrelated nature of these dynamics means that studying the simultaneous effect on households' financial distress of the historically worst values in these three variables would overestimate the effect of the crisis. To overcome this shortcoming we study the effect of the changes in the variables over a sequence of time periods from the start of the crisis in the first quarter of 2008 to the start of the recovery in the second quarter of 2010. The simulated dynamics in the shocked variables are presented in Figure A3 in Appendix 7. It should be noted that the starting values of the shocked variables were much different at the time of the survey to what they were in the pre-recession period, as interest rates were much higher at the beginning of the crisis for example than in 2013, which is the base in our simulation.[26] The unemployment rate was still higher in 2013 than it was before the crisis and real estate prices had not yet reached their pre-crisis level.

Assessment of the impact of simultaneous shocks using data from other countries has shown that reducing interest rates in the face of adverse macroeconomic shocks can be a very effective way of stopping households defaulting, as a reduction in interest rates can offset the negative effects from unemployment and asset prices (Bilston et al. (2015)).

The effect of the simultaneous shock is presented in Table 6 and Figure 10. The effect of this shock is comparable in size to those from the individual shocks of two standard deviations. The simulated variables follow similar dynamics to those in the historical data. Simulated EAD increases first due to the rise in the Euribor rate, then declines somewhat when the Euribor falls to zero, and starts to climb up again when unemployment starts to increase. The crisis has its strongest adverse effect on the household probability of default nine months after its outbreak, and the losses for banks reach their worst values at the same

[25] The crisis and adjustment in Estonia are described in e.g. Purfield and Rosenberg (2010)

[26] It is assumed that the Euribor will increase in the simulated shock as it did in 2008 and will then decline to zero; the effect of the negative Euribor on households' distress has not been simulated and it is assumed that all non-positive Euribor values will reduce the mortgage interest rates as far as the borrower's individual interest margin but no further.

time. The EAD increases from 3.4% to 5.1%, which is less than the historical reaction in our proxy of the non-performing loan rate. The LGD increases three and a half times from a rate of 0.4% to 1.5%, which is also smaller than the actual increase in provisions during the Great Recession.

There are two probable reasons why we find the reaction to the simulated crisis to be weaker. First, indebted households were more financially sound after the crisis. The crisis had to some extent a cleansing effect on the stock of indebted households, as the credit sustainability of households was tested in practice and households with non-sustainable loans exited the credit market. Second, our simulation model is not dynamic and is much more suitable for short-lived shocks. The long-lived shock of two and a half years can be simulated better in the dynamic model where the duration of shocks can be taken into account. For example our calibration in Section 5.1 implies that only a minority of households with a negative financial margin actually default, i.e. these who have financial assets worth less than one month's value of negative financial margin. However, the share of defaulting households may increase in a prolonged recession.

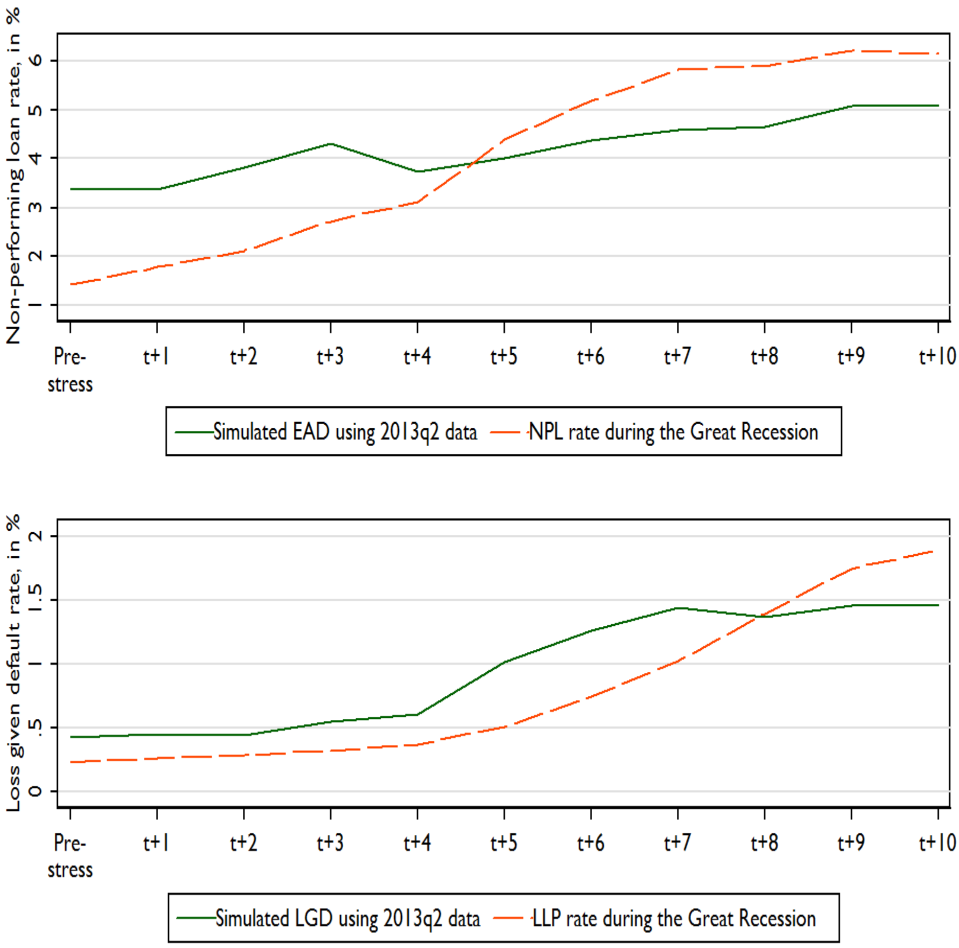

Figure 10: The effect of a simultaneous shock on exposure at default (EAD) and on loss given default (LGD); and comparison to historical developments in the non-performing loans (NPL) and loan loss provisions (LLP) of the banking sector

Note: The non-performing loan rate (NPL) refers to loans for which payments are delayed by 30 days or more.
Source: authors' calculations from the Estonian HFCS data; the Bank of Estonia statistics table 3.3.11 for non-performing loans; and the Bank of Estonia credit risk model for loan loss provisions.

The losses for banks from the housing sector increase to 71.3 million euros two and a half years after the outbreak of the crisis. This is a substantial increase given the pre-stress level of 20.6 million euros. The increase can be interpreted as the total cost of the crisis for the banks as we model the financial fragility of households in a static picture. The Estonian commercial banks made approximately 90 million euros in profits per quarter during the aftermath of the crisis, which indicates that the extra 50.7 million euros of losses from the household loans were easily absorbed by the banks. As shown in Appendix 4, the Great Recession led to much worse loan quality in the corporate sector than in the housing sector and this historical development is supported by our simulation, as the risks to financial stability from the housing sector appear to be limited.

6. Conclusions

The aim of this paper is to analyse the financial fragility of the Estonian household sector. We employ a stress test model in which the probability of default is evaluated on the basis of the ability of households to service debt from current income and the availability of financial buffers. The analysis is based on household-level data from the Estonian Household Finance and Consumption Survey (HFCS), which was conducted in 2013.

We derive a set of indicators to identify households that are financially distressed and analyse the sensitivity of financial sector loan losses to adverse shocks. This is the first paper that provides a comprehensive assessment of the financial vulnerability of the Estonian household sector and compares indicators of financial fragility based on the survey and on administrative data.

The paper identifies a number of findings. First, a relatively large number of Estonian households were financially distressed in 2013, but despite the high level of household distress the risks from the household sector to financial intermediation were small. The share of households with a negative financial margin varied from 13% to 37%, depending on how essential consumption expenditures were defined. Within this, 16% of households reported that their expenses had exceeded income in the previous 12 months and 17% indicated that they had experienced problems with servicing their debts in the same period. The estimated probabilities of default on household debt ranged from 5% to 17%, depending on which measure of household distress was used for the assessment. Although the share of households with financial difficulties was relatively large, the estimated loan losses of the banks were not substantial. Loss given default varied from 0.4% to 1.6% across various alternative measures. The historical loss given default rate for the same period, the second quarter of 2013, was 0.8%.

This relatively low level of the loan losses of the banks is surprising, given that not only was the share of households whose income was below expenditures rather large, but indebted households also had small financial buffers. The HFCS contains questions that aim to shed light on how households cope with financial difficulties. The responses to these questions indicate that Estonian households are more reliant on social networks than euro area households are on average. Among Estonian households, 45% reported that they would be able to get financial help from relatives or friends, while the corresponding share was 22% in the euro area. On the other hand, reliance on short-term financing was less prevalent in Estonia than in the euro area, as 10% of households in Estonia would use credit card debt and 5% would try to get other loans if they had debt servicing problems, while the same figures were 23% and 15% in the euro area.

Table 6: The effect of a simultaneous shock on the financial fragility of households

	Pre-stress	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Negative financial margin, %	13.0	13.0	13.4	14.3	14.0	15.0	16.0	16.8	17.1	18.3	18.3
Probability of default, %	5.2	5.1	5.4	5.9	5.7	6.1	6.6	6.9	7.0	7.5	7.5
Exposure at default, %	3.4	3.4	3.8	4.3	3.7	4.0	4.4	4.6	4.7	5.1	5.1
...mortgages, %	3.2	3.1	3.6	4.1	3.5	3.8	4.1	4.3	4.4	4.8	4.8
...non-collateralised loans, %	8.8	8.8	8.8	9.2	9.3	9.7	10.1	10.4	10.5	10.9	10.9
Exposure at default, mln EUR	165.9	164.9	186.6	210.6	182.7	196.2	213.9	223.8	227.7	247.8	248.1
...mortgages, mln EUR	147.4	146.4	168.1	191.3	163.3	176.0	192.8	202.2	205.9	225.0	225.2
...non-collateralised loans, mln EUR	18.5	18.5	18.5	19.3	19.4	20.2	21.1	21.7	21.9	22.8	22.8
Loss given default, %	0.4	0.4	0.4	0.5	0.6	1.0	1.3	1.4	1.4	1.5	1.5
...mortgages, %	0.0	0.1	0.1	0.2	0.2	0.6	0.9	1.0	1.0	1.0	1.0
...non-collateralised loans, %	8.8	8.8	8.8	9.2	9.3	9.7	10.1	10.4	10.5	10.5	10.9
Loss given default, mln EUR	20.6	21.7	21.5	26.6	29.6	49.3	61.3	70.2	66.5	71.0	71.3
...mortgages, mln EUR	2.1	3.2	3.0	7.3	10.2	29.1	40.2	48.5	44.6	48.2	48.5
...non-collateralised loans, mln EUR	18.5	18.5	18.5	19.3	19.4	20.2	21.1	21.7	21.9	22.8	22.8
No of obs	769.0	769.0	769.0	769.0	769.0	769.0	769.0	769.0	769.0	768.9	768.9

Source: Authors’ calculations from Estonian HFCS data.

Second, comparison with the administrative data indicates that Estonian households tend to overestimate their income and assets and underestimate their loan burden in the survey. We experimented with replacing the survey data with register data for household income, debt and assets, first one by one and then for all these variables together. The use of register data resulted in larger estimated household default rates and larger losses for the banks relative to the survey-based measures. However, the assessments based on the data from alternative sources did not alter the main conclusion that the estimated loan losses for banks from the household sector were modest.

Third, the stress-test elasticities of household default rates and banking sector loan losses were assessed separately for three standardised negative macroeconomic shocks: a rise in interest rates, an increase in the unemployment rate, and a fall in real estate prices. The stress-testing of Estonian households implied that shocks to unemployment and interest rates were the main source of household distress, while losses for the banking sector were the highest from real estate price shocks.

Shocking the interest rates and the unemployment rate resulted in only mild changes in the probability of households defaulting and the loss given default of the banks. Increases in the probability of default were somewhat stronger in response to the unemployment rate shocks, which is a similar finding to that for other Central and Eastern European countries where job losses generally result in a larger drop in income than in Western European countries (Galuscak et al. (2016), Johansson and Persson (2006)).

By construction, the real estate price shocks have no effect on the probability of default and only affect the loss given default rates of the banks. Although a decline in real estate prices had a stronger effect on estimated loan losses than the interest rate and unemployment rate shocks did, the impact was still rather mild. This is a surprising finding, given the large historical variation in Estonian real estate prices, which meant that the shocks of one, two and three standard deviations that we applied led to very strong declines in house prices of 24%, 49% and 73%, accordingly. The stress testing results were confirmed by the aggregate historical dynamics of the financial stability indicators in Estonia, which also showed that the Estonian banking sector experienced low loan loss provision (LLP) rates and almost negligible write off rates throughout the recent financial crisis.

In the second stage of the stress-testing evaluation we estimated the impact of a simultaneous shock to all three above-named variables, which mimicked their movements during the Great Recession period covering the ten quarters starting from the first quarter of 2008. The resulting increases in the non-performing loan (NPL) rate and the loss given default rate were somewhat milder than the actual historical increases in the NPL and LLP rates in this period. The effect from the model was more stable than the historic trends of these variables because households were on average more financially solvent in 2013 than during the crisis. In addition, our simulation model is not dynamic and so it is better suited for assessing the effects of short-lived shocks.

Fourth, the household characteristics that were most correlated with financial fragility were income and education. We assessed the financial fragility across different household types. Household income was strongly negatively related with the probability of default as households in the first and second income quintiles were substantially more likely to default on their loans than more affluent households were. This result was confirmed by multivariate analysis, which also showed a significant negative link between income and various measures of the probability of default. The education level of the household reference person also played a role as a higher level of education resulted in fewer problems with loan servicing.

The stress-testing framework used in this paper can be extended to assess the impact of changes in other variables, such as taxes or consumer prices. In the future, similar stress testing exercises can be repeated using updated versions of the HFCS data. It is possible to build either on the future waves of the survey data, which will be collected at three-year intervals, or on simulated data, which can be computed with a higher frequency.

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Appendix 1: Indicators of financial fragility: Definitions[27]

Debt-to-asset ratio: Ratio of total liabilities (debt) to total assets. Defined for indebted households.

Debt-to-income ratio: Ratio of total liabilities to total annual gross household income. Defined for indebted households.

Debt service ratio: Ratio of total monthly debt payments to household gross monthly income. Defined for indebted households. The debt payments for credit lines/overdraft debt and credit card debt are not covered, since this information was not collected in the HFCS.

Loan-to-value ratio of the HMR: Ratio of the outstanding balance of the HMR mortgage to the current value of the HMR. Defined for households with HMR mortgages.

The ratio of net liquid assets to income: Ratio of net liquid assets to total annual gross household income. Net liquid assets are calculated as the sum of the value of deposits, mutual funds, bonds, non-self-employment business wealth, and publicly traded shares; net of credit line / overdraft debt, credit card debt and other non-mortgage debt. Defined for all households.

[27] The source of the definitions is "The Eurosystem Household Finance and Consumption Survey Results from the First Wave", published by the Eurosystem Household Finance and Consumption Network, 2013.

Appendix 2: Financial burden indicators and loan and household characteristics

Table A2: The relationship between financial burden indicators and loan and household characteristics

	log(debt-to-asset ratio)	log(debt-to-income ratio)	log(debt-service-to-income ratio)	log(loan-to-value ratio of HMR)	log(liquid assets-to-income ratio of indebted hhs)
Type of debt (base mortgage only)					
Mortgage and non-collateralised debt	1.840***	2.990***	1.210***	–0.119	0.151
	(0.255)	(0.228)	(0.150)	(0.137)	(0.501)
Non-collateralised debt	1.934***	3.074***	1.436***	NA	–0.220
	(0.266)	(0.236)	(0.159)		(0.519)
Number of mortgages					
2 or more (base else)	–0.196	–0.377***	–0.296***	–0.232	0.732**
	(0.171)	(0.146)	(0.082)	(0.158)	(0.364)
Year when largest loan taken (base 2002 or before)					
2003	–0.138	–0.080	0.446	–0.078	0.798
	(0.446)	(0.438)	(0.273)	(0.400)	(0.651)
2004	0.293	0.240	0.278	0.462	0.220
	(0.371)	(0.364)	(0.254)	(0.321)	(0.723)
2005	0.694**	0.731**	0.489*	0.826***	0.210
	(0.326)	(0.334)	(0.251)	(0.278)	(0.542)
2006	0.747**	1.165***	0.663***	0.894***	0.477
	(0.328)	(0.314)	(0.243)	(0.296)	(0.550)
2007	0.805**	0.911***	0.552**	0.829***	0.578
	(0.329)	(0.320)	(0.242)	(0.280)	(0.528)
2008	0.770**	0.759**	0.441*	0.823***	0.612
	(0.347)	(0.335)	(0.248)	(0.307)	(0.626)
2009	0.620	1.034**	0.802***	0.779**	1.184*
	(0.408)	(0.434)	(0.267)	(0.342)	(0.665)
2010	0.620*	1.127***	0.759***	0.835***	0.961
	(0.347)	(0.361)	(0.277)	(0.311)	(0.657)
2011	0.602	0.772**	0.721***	0.783***	0.820
	(0.398)	(0.337)	(0.253)	(0.299)	(0.623)
2012	0.579	0.920**	0.724**	0.883***	0.946*
	(0.374)	(0.396)	(0.297)	(0.331)	(0.569)
2013	0.884**	1.167***	0.729**	1.120***	0.864
	(0.435)	(0.411)	(0.309)	(0.361)	(0.598)
Household size (base 1)					
2	–0.511*	–0.342	–0.016	–0.256	0.411
	(0.273)	(0.246)	(0.183)	(0.214)	(0.394)
3	–0.492*	–0.377	–0.119	–0.057	0.461
	(0.253)	(0.236)	(0.169)	(0.204)	(0.389)
4	–0.220	–0.222	–0.003	0.000	0.709*
	(0.279)	(0.236)	(0.164)	(0.205)	(0.383)
5 and More	–0.559**	–0.440*	–0.089	–0.328	0.455
	(0.269)	(0.253)	(0.171)	(0.247)	(0.478)

	log(debt-to-asset ratio)	log(debt-to-income ratio)	log(debt-service-to-income ratio)	log(loan-to-value ratio of HMR)	log(liquid assets-to-income ratio of indebted hhs)
Housing status (base owner)					
Renter	1.267***	–0.111	0.082	NA	0.297
	(0.308)	(0.222)	(0.170)		(0.464)
Percentile of Income (base Less than 20)					
20–39	–0.586	–1.850***	–1.396***	0.119	–2.910***
	(0.518)	(0.458)	(0.354)	(0.421)	(0.756)
40–59	–0.340	–2.143***	–1.895***	–0.094	–2.946***
	(0.450)	(0.452)	(0.342)	(0.418)	(0.774)
60–79	–0.538	–2.623***	–2.318***	–0.118	–2.702***
	(0.421)	(0.413)	(0.311)	(0.404)	(0.729)
80–100	–0.395	–2.966***	–2.719***	0.041	–3.177***
	(0.408)	(0.399)	(0.298)	(0.395)	(0.738)
Percentile of Net Wealth (base Less than 20)					
20–39	–2.108***	–0.436*	–0.139	–0.566***	–0.267
	(0.278)	(0.250)	(0.184)	(0.167)	(0.460)
40–59	–2.633***	–0.622**	–0.182	–1.103***	0.747*
	(0.269)	(0.255)	(0.163)	(0.188)	(0.382)
60–79	–2.853***	–0.591***	–0.197	–1.296***	1.093**
	(0.271)	(0.224)	(0.168)	(0.165)	(0.449)
80–100	–3.553***	–0.427*	–0.171	–1.711***	1.732***
	(0.284)	(0.218)	(0.172)	(0.210)	(0.444)
Age of Reference Person (base 16–34)					
35–44	0.101	–0.027	0.083	–0.149	–0.170
	(0.211)	(0.205)	(0.148)	(0.123)	(0.281)
45–54	–0.476***	–0.365*	0.025	–0.457***	–0.316
	(0.182)	(0.192)	(0.125)	(0.165)	(0.294)
55–64	–0.342	–0.438*	0.124	–0.746***	–0.685*
	(0.251)	(0.229)	(0.162)	(0.263)	(0.391)
65–74	–0.940**	–0.932***	0.048	–0.836**	–0.455
	(0.399)	(0.327)	(0.283)	(0.421)	(0.765)
75+	–0.883	–0.800	–0.303	–2.014	0.023
	(0.972)	(0.817)	(1.074)	(1.399)	(1.961)
Work Status of Reference Person (base Employee)					
Self-Employed	0.027	0.394	0.242	0.314**	–0.412
	(0.218)	(0.251)	(0.222)	(0.157)	(0.353)
Retired	–0.063	–0.325	–0.703***	0.250	–0.032
	(0.491)	(0.348)	(0.260)	(0.672)	(0.856)
Other Not Working	0.391	–0.002	–0.051	–0.201	–0.020
	(0.345)	(0.343)	(0.281)	(0.234)	(0.568)
Education of Reference Person (base primary or less)					
Secondary	0.219	0.606*	0.223	0.238	1.631***
	(0.332)	(0.317)	(0.240)	(0.221)	(0.539)
Tertiary	0.345	0.797***	0.254	0.357	2.459***
	(0.317)	(0.302)	(0.230)	(0.231)	(0.537)
No of obs	737	737	725	493	617

Notes: Ordinary least square estimates using multiply imputed data of five implicates and 1000 replicate weights. NA means not applicable. *, **, and *** refer to statistical significance at the 10, 5, and 1 per cent levels of significance.
Source: Authors' calculations from the Estonian HFCS data.

Appendix 3: Distribution of the financial margin across debt types

Table A3: Participation, percentiles and mean values of financial margin

	Share in populati on	Share with negative value	p5	p25	p50	p75	p95	mean
No debt	0.695	0.071	–81.0	164.4	377.5	700.2	1 719.9	572.0
Mortgage debt	0.173	0.112	–148.6	322.4	856.6	1 515.3	3 117.9	1 096.4
Mortgage and non-collateralised debt	0.034	0.045	73.8	521.5	911.6	1 442.7	2 824.8	1 154.7
Non-collateralised debt	0.098	0.189	–207.4	76.1	355.9	706.5	1 508.0	472.7

Source: Authors’ calculations from the Estonian HFCS data.

Appendix 4: Historical developments in loan quality and banking sector losses

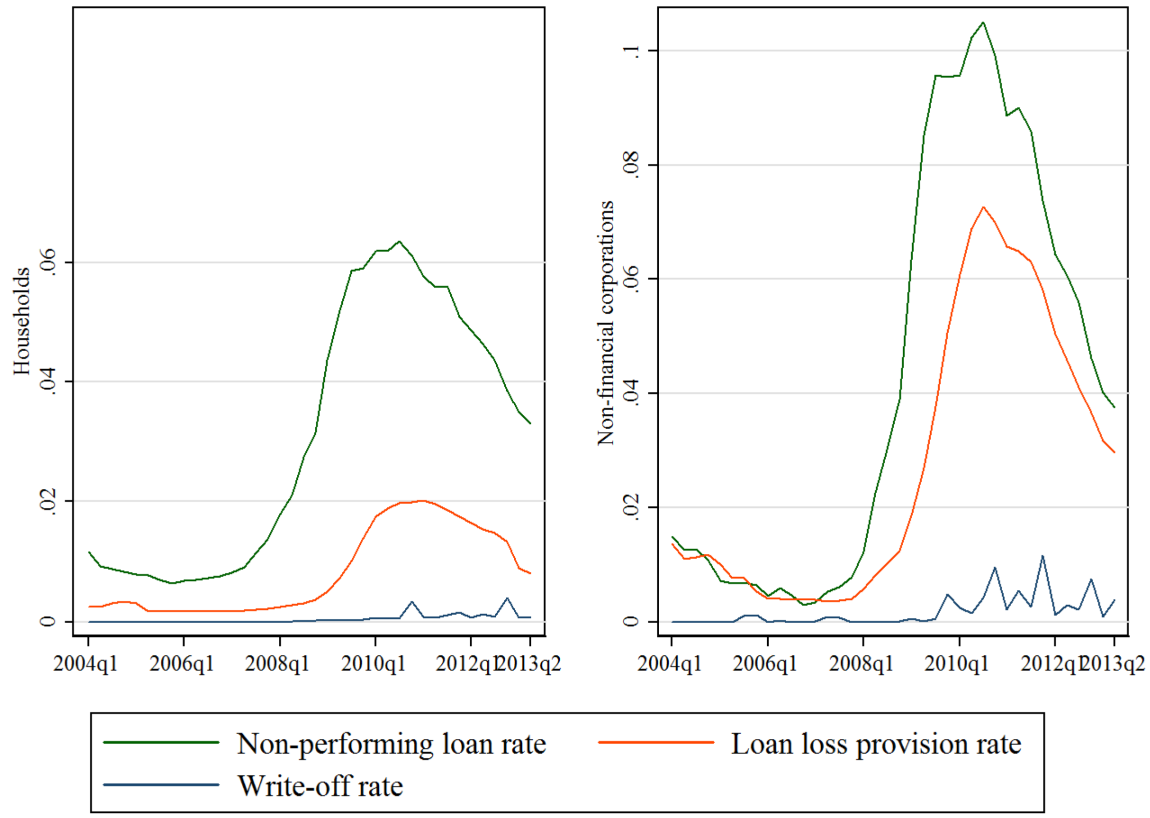

Figure A1: Non-performing loan rates, loan loss provision rates and write-off rates, 2004q1–2013q2

Note: The non-performing loan rate is based on loans past due by more than 30 days.
Source: the Bank of Estonia statistics table 3.3.11 for the non-performing loans; and the Bank of Estonia credit risk model for loan loss provisions and write-offs.

Appendix 5: Correlation between alternative measures of probability of default

Table A4: Pearson correlation coefficients

	(1) Baseline: C = subsistence minimum	(2) C = food and utilities	(3) C = food, utilities and other non-durables	(4) Debt repayment problems in last 12 months	(5) Expenses exceeded income in last 12 months [b)]	(6) Registers: C = subsistence minimum	Number of observations
(1)	1						769
(2)	0.671***	1					769
(3)	0.550***	0.823***	1				769
(4)	0.298***	0.289***	0.298***	1			769
(5)	0.213***	0.363***	0.414***	0.296***	1		760
(6)	0.291***	0.255***	0.206***	0.157***	0.098**	1	687

Notes: *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels of significance.
Source: Authors' calculations from the Estonian HFCS and administrative data.

Appendix 6: Alternative measures of the probability of default and household characteristics

Table A5: The relationship between alternative measures of the probability of default and household characteristics

	Dependent variable is the probability of default using:				
	Baseline: C = subsistence minimum	C = food and utilities	C = food, utilities and other non-durables	Debt repayment problems in last 12 months[a)]	Expenses exceeded income in last 12 months [b)]
Type of debt (base mortgage only)					
Mortgage and non-collateralised debt	0.001	0.013	–0.021	0.060	–0.007
	(0.027)	(0.055)	(0.065)	(0.061)	(0.054)
Non-collateralised debt	0.001	0.023	0.042	0.131**	–0.015
	(0.029)	(0.056)	(0.069)	(0.058)	(0.053)
Number of mortgages					
2 or more (base else)	0.015	–0.003	–0.001	–0.101*	–0.018
	(0.018)	(0.040)	(0.046)	(0.060)	(0.042)
Year when largest loan taken (base 2002 or before)					
2003	0.038	0.039	0.064	0.153	–0.102*
	(0.037)	(0.056)	(0.077)	(0.115)	(0.056)
2004	0.059	0.052	0.065	0.029	–0.076
	(0.037)	(0.052)	(0.067)	(0.063)	(0.057)
2005	0.047	0.124**	0.153**	0.145*	0.037
	(0.039)	(0.058)	(0.062)	(0.084)	(0.064)
2006	0.073*	0.076	0.079	0.169***	–0.061
	(0.038)	(0.054)	(0.059)	(0.053)	(0.056)
2007	0.067*	0.068	0.053	0.118**	–0.039
	(0.039)	(0.051)	(0.058)	(0.058)	(0.058)
2008	0.068	0.008	–0.021	0.136*	–0.049
	(0.044)	(0.054)	(0.062)	(0.081)	(0.064)
2009	0.088**	0.034	0.040	0.230***	–0.024
	(0.044)	(0.051)	(0.067)	(0.080)	(0.070)
2010	0.065*	0.046	0.022	0.070	–0.054
	(0.039)	(0.052)	(0.058)	(0.114)	(0.064)
2011	0.050	0.051	0.062	0.139	0.005
	(0.044)	(0.062)	(0.073)	(0.086)	(0.074)
2012	0.055	0.048	0.058	0.099*	–0.067
	(0.042)	(0.054)	(0.067)	(0.051)	(0.062)
2013	0.076*	0.060	0.040	0.055	–0.100
	(0.046)	(0.057)	(0.068)	(0.056)	(0.064)
Household size (base 1)					
2	–0.021	–0.015	–0.061	0.079	–0.025
	(0.027)	(0.045)	(0.052)	(0.052)	(0.044)
3	0.006	–0.003	–0.089*	0.052*	–0.039
	(0.030)	(0.043)	(0.052)	(0.030)	(0.046)
4	0.010	0.001	–0.051	0.073	–0.078*
	(0.030)	(0.046)	(0.054)	(0.051)	(0.044)
5 and More	–0.014	–0.039	–0.109**	0.092	–0.033
	(0.032)	(0.046)	(0.055)	(0.059)	(0.054)

	Dependent variable is the probability of default using:				
	Baseline: C = subsistence minimum	C = food and utilities	C = food, utilities and other non-durables	Debt repayment problems in last 12 months[a)]	Expenses exceeded income in last 12 months [b)]
Housing status (base owner)					
Renter	0.007	–0.008	–0.018	0.074	–0.031
	(0.038)	(0.066)	(0.065)	(0.083)	(0.048)
Percentile of Income (base Less than 20)					
20–39	–0.242***	–0.091	0.057	–0.090	–0.010
	(0.088)	(0.108)	(0.099)	(0.105)	(0.084)
40–59	–0.409***	–0.371***	–0.301***	–0.152	–0.036
	(0.074)	(0.086)	(0.089)	(0.114)	(0.083)
60–79	–0.398***	–0.432***	–0.332***	–0.208	–0.103
	(0.076)	(0.086)	(0.086)	(0.127)	(0.082)
80–100	–0.404***	–0.457***	–0.389***	–0.271**	–0.151*
	(0.076)	(0.084)	(0.085)	(0.116)	(0.079)
Percentile of Net Wealth (base Less than 20)					
20–39	–0.039	–0.032	–0.022	–0.018	–0.032
	(0.042)	(0.067)	(0.065)	(0.077)	(0.067)
40–59	–0.019	–0.092	–0.083	–0.123	–0.062
	(0.044)	(0.067)	(0.064)	(0.079)	(0.051)
60–79	–0.034	–0.078	–0.070	–0.138	–0.034
	(0.037)	(0.061)	(0.057)	(0.086)	(0.060)
80–100	–0.020	–0.058	–0.058	–0.096	–0.033
	(0.038)	(0.063)	(0.060)	(0.082)	(0.056)
Age of Reference Person (base 16–34)					
35–44	0.027	0.033	0.017	0.087**	0.037
	(0.022)	(0.030)	(0.035)	(0.039)	(0.029)
45–54	0.044**	0.052	0.042	0.096	0.001
	(0.022)	(0.039)	(0.042)	(0.060)	(0.031)
55–64	0.057**	–0.000	–0.011	0.094*	–0.037
	(0.029)	(0.042)	(0.046)	(0.051)	(0.034)
65–74	0.008	–0.013	–0.035	0.096	–0.141**
	(0.041)	(0.070)	(0.085)	(0.140)	(0.064)
75+	0.084	–0.078	–0.279	0.332	–0.152
	(0.077)	(0.138)	(0.173)	(0.249)	(0.111)
Work Status of Reference Person (base Employee)					
Self-Employed	0.030	0.029	0.078	–0.014	0.049
	(0.033)	(0.042)	(0.057)	(0.070)	(0.043)
Retired	–0.196***	–0.238***	–0.140	–0.113*	0.006
	(0.054)	(0.079)	(0.104)	(0.061)	(0.081)
Other Not Working	0.034	–0.016	0.053	0.111	0.011
	(0.053)	(0.057)	(0.063)	(0.078)	(0.066)
Education of Reference Person (base primary or less)					
Secondary	–0.060	–0.071	–0.137***	0.016	–0.090*
	(0.042)	(0.048)	(0.053)	(0.072)	(0.054)
Tertiary	–0.081*	–0.116**	–0.198***	–0.057	–0.104*
	(0.042)	(0.048)	(0.052)	(0.073)	(0.053)
No of obs	737	737	737	737	728

Notes: Ordinary least square estimates using multiply imputed data of five implicates and 1000 replicate weights. [a)] Logit model marginal effects using mimrgns command for Stata. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels of significance.
Source: Authors' calculation from the Estonian HFCS data.

Appendix 7: Dynamics of macro variables and assumptions of a simultaneous shock

Figure A2: Dynamics of the historical macro variables in Estonia, 2004q1–2013q2

Notes: All variables except the six-month Euribor are seasonally adjusted. The period highlighted by the red vertical lines is the stress period simulated by the simultaneous shock.
Source: the Statistics Estonia and Bank of Estonia macromodel EMMA.

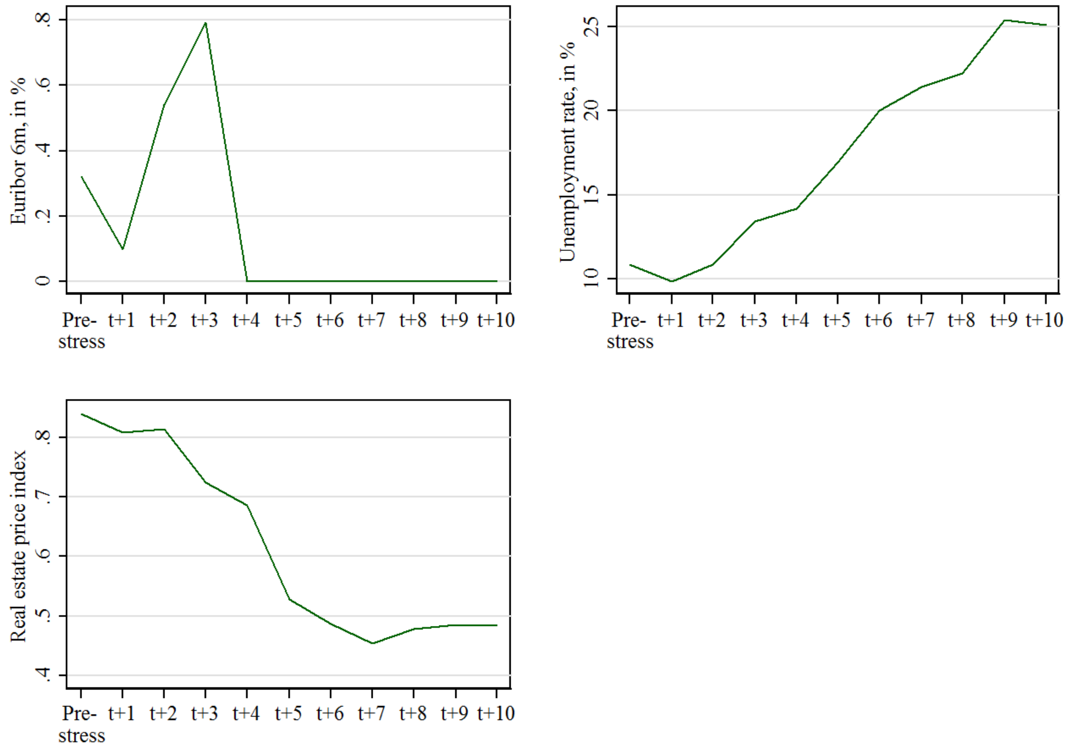

Figure A3: Dynamics of the simulated simultaneous shock

Notes: All variables except the six-month Euribor are seasonally adjusted. Pre-stress refers to values in 2013q2; the period t+1 to t+10 mimics the dynamics of the macro variables in the Great Recession from 2008q1 to 2010q2.
Source: Authors' calculations using data from the Statistics Estonia and Bank of Estonia macromodel EMMA.

Appendix 8: Probability of being unemployed and personal characteristics

Table A6: The relationship between unemployment and personal characteristics, average marginal effects from the logit model

	Dependent variable: unemployed = 1, employed = 0
Male (base female)	0.028**
	(0.013)
Age	0.003
	(0.003)
Age squared / 100	–0.004
	(0.004)
Married (base other)	–0.049***
	(0.015)
Estonian ethnicity (base other)	–0.089***
	(0.019)
Education secondary (base primary)	–0.136***
	(0.032)
Education tertiary (base primary)	–0.176***
	(0.033)
County Harju (base Tallinn)	–0.005
	(0.019)
County Hiiu (base Tallinn)	–0.037
	(0.026)
County Ida-Viru (base Tallinn)	0.111***
	(0.029)
County Jõgeva (base Tallinn)	–0.011
	(0.042)
County Järva (base Tallinn)	0.018
	(0.055)
County Lääne (base Tallinn)	–0.016
	(0.037)
County Lääne-Viru (base Tallinn)	0.033
	(0.036)
County Põlva (base Tallinn)	0.157
	(0.097)
County Pärnu (base Tallinn)	0.038
	(0.032)
County Rapla (base Tallinn)	0.066
	(0.072)
County Saare (base Tallinn)	0.009
	(0.046)
County Tartu (base Tallinn)	0.005
	(0.024)
County Valga (base Tallinn)	–0.005
	(0.049)
County Viljandi (base Tallinn)	–0.017
	(0.036)
County Võru (base Tallinn)	0.063
	(0.044)
No of obs	2790

Notes: Logit estimates using multiply imputed data of five implicates and 1000 replicate weights. Standard errors are reported in brackets and are clustered at the household level. Using mimrgns command for Stata to calculate marginal effects. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels of significance.
Source: Authors' calculations from the Estonian HFCS data.

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