Stress Tests of the Household Sector Using Microdata from Survey and Administrative Sources*

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This paper conducts microsimulation-based stress tests to assess the financial risks of the household sector. The Estonian Household Finance and Consumption Survey data set is employed, where the survey data from household interviews are complemented with the same information from administrative registers. We analyze the sensitivity of financial-sector loan losses to adverse shocks. It is found that the survey data and the register data indicate the same segment of vulnerable households. The main difference between the two data sources is that the losses predicted by the register data are larger. This is mostly the result of the overestimation of assets and underestimation of liabilities in the survey.

JEL Codes: D14, E43, G21, C81.

1. Introduction and Related Literature

Household borrowing has increased considerably in most European countries in recent decades, both in absolute terms and in relation to household income. The rapid increase in household debt in the United States was one of the triggers of the Great Recession (e.g., Mian and Sufi 2010). These developments have been the source of concerns about the financial system and have led many central banks to undertake stress-testing exercises to assess the resilience of the household sector to various macroeconomic

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risks. Earlier analyses of financial stability were almost exclusively based on macrodata, but recently they have increasingly been conducted on disaggregated data. The use of microlevel statistics on household finances has several advantages over macrolevel studies. It allows the extent of households' financial buffers to be assessed together with their liabilities and makes it possible to evaluate the distribution of the debt burden across different household types.

As part of the initiative to base financial stability analysis on disaggregated data, the euro-area central banks together with the European Central Bank launched the Household Finance and Consumption Survey. This survey collects data on households' assets and liabilities in a harmonized manner across all the euro-area countries. These data are representative at both the national and euro-area levels and contain comprehensive information on households' balance sheets. The availability of the Household Finance and Consumption Survey data makes it possible to conduct microdata-based studies of households' ability to service their debts and of the credit risks to the financial sector that emanate from the household sector. Several recent studies focus on financial fragility analysis using the Household Finance and Consumption Survey data or analogous microlevel data sets.[1]

While most of the countries collect household balance sheet data by interviewing households, there is an increasing tendency to compile such databases on the basis of administrative sources.[2] The aim

[1]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, Liu, and Roberts (2012) for Canada; Martinez et al. (2013) for Chile; Michelangeli and Pietrunti (2014) for Italy; Bańbula et al. (2015) for Poland; Bilston, Johnson, and Read (2015) for Australia; Ampudia, van Vlokhoven, and Zochowski (2016) for 10 euro-area countries; and Galuščák, Hlaváč, and Jakubík (2016) for the Czech Republic.

[2]Finland is the only country that relies mostly on administrative register data in the Household Finance and Consumption Survey (Eurosystem Household Finance and Consumption Network 2016). Register data-based household stress testing is already used by the Danish central bank (Andersen et al. 2013). The European Central Bank plans to launch an analytical credit data set (AnaCredit) that will collect whole population-based corporate- and housing-sector loan-level data that can be used for stress testing (Israel et al. 2017).

of our paper is to construct households' financial fragility indicators and conduct stress-testing exercises using and comparing data from different sources, i.e., from interviews and from administrative registers. To the best of our knowledge, ours is the first paper to conduct such a comparison. This lets us evaluate whether different data-collection methods yield different messages in the assessment of the financial risks of the household sector.

As a general rule, the Household Finance and Consumption Survey data were collected by household interviews, but some euro-area countries partially complemented or replaced survey data with variables from administrative sources. While this was mostly done only partially, the Household Finance and Consumption Survey data set for one country, Estonia, contains comprehensive information on households' assets, liabilities, and incomes from two separate sources, i.e., from administrative files as well as from the survey. We employ the Estonian Household Finance and Consumption Survey data set to conduct stress tests of households' financial fragility using both the survey data and the administrative records.

Being able to access the data from these two alternative sources lets us evaluate possible biases in the survey-based estimates of household incomes, liabilities, and assets relative to the administrative data. While there are many studies which compare incomes from surveys and administrative sources (e.g., Duncan and Hill 1985; Pischke 1995; Bound, Brown, and Mathiowetz 2001; Kapteyn and Ypma 2007; Chen, Hong, and Nekipelov 2011), there are only a few papers that provide a similar comparison for households' net wealth (e.g., Johansson and Klevmarken 2007). A comparison of liabilities is also given in only a limited number of studies (e.g., Brown et al. 2011). To the best of our knowledge, there is no study that uses all the information about income, assets, and liabilities and compiles financial fragility indicators for households from survey and register data.

This paper conducts stress tests of the household sector by quantifying the effect of various adverse shocks on household finances and by assessing the ability of households to continue servicing their debts after they have been exposed to shocks. In addition, we look at the distributional aspects of financial distress by detecting groups of households which are more financially fragile or are particularly vulnerable to adverse shocks. The estimation methodology that we use in the stress-testing exercises builds on approaches that were used by the earlier studies, which employed microlevel data to assess the financial risks of the household sector.

The earlier papers that evaluate households' financial vulnerability can be divided into three groups. The first approach assesses financial fragility by finding the fraction of households whose ratio of debt service to income exceeds some threshold level. Most typically, households are considered financially fragile when their ratio of debt service to income exceeds 30 percent, but some authors also use 35 percent or 40 percent. Examples of the studies using this approach include Faruqui, Liu, and Roberts (2012), Martinez et al. (2013), and Michelangeli and Pietrunti (2014).

The second method is based on the share of households with a negative financial margin. The financial margin is defined as current disposable income from which essential consumption expenditures and loan servicing costs are deducted. In these studies, it is typically assumed that all households with negative financial margins will default on their loans. This approach is used in, e.g., Johansson and Persson (2006), Holló and Papp (2007), and Albacete and Fessler (2010).

The third method considers the share of liquid assets the household has in addition to the financial margin when determining the likelihood of the household defaulting on its loans. This method is used, e.g., in recent studies by Ampudia, van Vlokhoven, and Zochowski (2014, 2016). Earlier studies of household stress tests assumed that the probability of defaulting on loans equals one for all households with a negative financial margin. However, in practice, only some households with a current negative financial margin default on their loans, since the probability of default is also dependent on the extent of the financial buffers they have in the form of liquid assets. In the approach used by Ampudia, van Vlokhoven, and Zochowski (2014, 2016), households will default on their loans only when they have negative financial margins and when the amount of liquid assets they have is smaller than a particular threshold value. This threshold value is calibrated so that the aggregate share of defaulted loans is equal to the actual share of nonperforming household loans in the banking sector for the same time period.

Our stress-testing methodology is closest to that used in the study by Ampudia, van Vlokhoven, and Zochowski (2016).

Specifically, we follow their idea of calibrating the probabilities of default for households so that the microdata-based exposure at default matches the aggregate historical share of households' non-performing loans (NPLs) in the banking sector.

The structure of the stress-testing exercises that is employed in this paper is similar to that in earlier studies which conducted stress tests. We use the following steps. First, the probability of default on household loans is assessed using survey and register data. Second, we simulate the effects of adverse shocks of one, two, and three standard deviations. The variables to which the shocks are applied are the base interest rate, the unemployment rate, and real estate prices. The next step is to assess the effect of these shocks on households' probability of default (PD). Finally, the resulting effect on the banks' household loan portfolios is evaluated by calculating the effect on the share of loans exposed to default (the exposure at default, or EAD) and on the resulting losses from defaulted loans (the loss given default, or LGD). The stress-testing exercises are performed using the survey data as well as the data from administrative files, which lets us compare the sensitivity of the results to the use of different data sources.

The biases in the survey data of the Estonian Household Finance and Consumption Survey are similar in many ways to those detected by the earlier studies, but we also identify some differences. First, we evaluate the level of indebtedness on the basis of the survey and compare it with data from the administrative files. We find no systematic bias in the reporting of the outstanding amounts of mortgage loans, i.e., survey and administrative records yield similar estimated outstanding amounts of mortgage loans on average. A similar comparison for noncollateralized loans shows that their amounts are underestimated in the survey relative to administrative records. This finding is in correspondence with the results of an earlier study in which data from the U.S. Survey of Consumer Finances are compared with administrative records, and which also shows that consumer loans tend to be underreported in surveys (Brown et al. 2011).

The estimated value of household assets is mainly determined by their real estate holdings, as real estate is by far the largest component of the assets of the average household (Eurosystem Household

Finance and Consumption Network 2013b). Comparing the register-based estimates with those reported by the survey respondents shows that households tend to overestimate the value of their real estate in the Estonian Household Finance and Consumption Survey. This result is in line with findings in some previous studies, which also imply that real estate values are upward biased in household surveys (e.g., Kiel and Zabel 1999, Johansson and Klevmarken 2007). Interestingly, conducting these comparisons for different types of real estate in the Estonian Household Finance and Consumption Survey implies that households tend to overestimate the value of their main residence, whereas their other real estate holdings are undervalued in the survey.[3]

In addition, we are able to compare the survey-based estimates of household incomes in the Estonian Household Finance and Consumption Survey with estimates based on the register data. Earlier studies have mostly found that incomes tend to be underreported in surveys, but the measurement error is usually negatively correlated with income level, i.e., low-income households tend to overreport their incomes and high-income households tend to underreport theirs in the survey (e.g., Rodgers, Brown, and Duncan 1993; Bound et al. 1994; and Pischke 1995). The negative correlation between the measurement error and the level of income is also present in the Estonian Household Finance and Consumption Survey. In the Estonian Household Finance and Consumption Survey, however, the register-based estimates of income are, on average, smaller than the survey-based estimates, which is an atypical finding.

Since survey-based estimates of income and assets are overvalued while liabilities are undervalued in the Estonian Household Finance and Consumption Survey, replacing the survey data with register data results in larger estimated measures of financial distress for the household sector and larger losses from defaults on household debts for the banking sector. The estimated losses for banks are up to four times larger in the stress tests based on register data than according to the survey data. Both data sources point to the same

[3]Main residences make up by far the largest part of households' real estate holdings. Therefore the overvaluation effects dominate and, on average, real estate holdings are overvalued.

segment of vulnerable households, indicating that low-income households bear most of the risks from household debts. The probability of default and the vulnerability to shocks is more concentrated to low-income households according to the survey data than it is according to the register data. These findings have potential implications for other similar studies. As a general rule, most of the earlier analyses of financial fragility have been based on survey data, and so it is likely that these evaluations underestimated the financial risks of the household sector. It is also relevant for cross-country comparisons, since if some of the country studies are based on administrative files and others on survey data, then the results are not directly comparable.

The paper is structured as follows. The second section describes the Estonian Household Finance and Consumption Survey data used for the analysis. The third section presents the derivation of the measures of financial fragility for households that are used in the stress tests and a comparison of these variables based on survey and administrative data. The fourth section presents the results of the stress-testing exercises using the survey and administrative data, and the last section provides the conclusions.

2. The Data

The Household Finance and Consumption Survey data set 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 unique feature of the Estonian Household Finance and Consumption Survey data is that the information collected by the survey was complemented by information from administrative registers, which allows the data from different sources to be compared and potential biases in reporting to the surveys to be estimated. There is no reason to believe that the results based on the survey and administrative data are unique to Estonia. Estonia is a representative case because the collection of the survey data was well harmonized with the other euro-area countries and was undertaken by the National Statistical Institution. Estonia is a European Union (EU) member state with a harmonized institutional setting of financial intermediation, and the level of its debt burden is at the average among the euro-area countries, although household debts have been accumulated more recently than in most of the other euro-area countries (Meriküll and Rõõm 2016, Kukk 2019).

The fieldwork for the Estonian Household Finance and Consumption Survey took place between March and June 2013, and the final sample contains 2,220 households. The sampling design was one-stage stratified systematic sampling. Wealthy households were oversampled in the survey to give better coverage of households' assets. The survey mode was computer-assisted personal interviews. The estimation weights were calculated to adjust for survey nonresponse and were calibrated for age, sex, degree of urbanization, ethnicity, education, household size, and homeownership status. Replicate weights were introduced for variance estimation, and bootstrap methods with replacement were used to create 1,000 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. The methodology for calculating the weights and for the imputation was similar to that used in other euro-area countries participating in the Household Finance and Consumption Survey; see Eurosystem Household Finance and Consumption Network (2013a) for more details. A more detailed explanation of the sample statistics of the Estonian Household Finance and Consumption Survey is given in Meriküll and Rõõm (2016).

A large number of survey items were also collected from administrative sources in Estonia. This served more than one purpose. The first aim was to validate the data collected by interviews. Second, the administrative data were used for the imputation of the missing observations. Third, the data from alternative sources were collected with the longer-term objective of gradually replacing the items collected from the interviews with administrative information in future waves of the survey. It is important for the context of this paper that in the editing process of the survey data set, the survey variables were mainly compiled using the information collected by interviews, so that the survey data and administrative data can be meaningfully compared. The only wealth component that was replaced in the survey with administrative data was the amount of financial assets held domestically. Financial assets mainly consist of bank deposits in Estonia and make up 10 percent on average of the gross value of all financial plus real assets.

The main administrative sources of data on disposable income were the Income and Social Security Tax Register, the Social Transfers Register, the Health Insurance Benefits Register, and the Unemployment Fund Register. Data from the Land Board were used for the estimates of real estate prices, data from the commercial banks were used for the outstanding amounts of deposits and financial liabilities, and data from the Central Register of Securities were used for the value of other financial assets. The administrative data were collected by Statistics Estonia and the Bank of Estonia and merged with the interview data collected from the household survey. All the variables from administrative sources were collected at the individual or household level.

The data that we use for comparative purposes are similar to those used in other studies comparing income and wealth data from survey and administrative sources (e.g., Johansson and Klevmarken 2007). The estimated values of financial assets and liabilities that are based on the administrative data are not completely free of measurement error, but they can be expected to be much closer to the true values of these variables than the survey-based estimates. The register-based estimates of income, on the other hand, are more likely to contain systematic measurement errors. The income data from the administrative sources may be underestimated because of tax evasion, as the share of wages that are undeclared has been estimated at 5–20 percent in Estonia (Putnins and Sauka 2015), and the share of undeclared self-employment income has even been put as high as 60 percent (Kukk and Staehr 2014). Furthermore, it is not clear whether respondents report the true value of their income in surveys or give the same income as that reported to the tax office. Households' choices about how much of their true income to report depend partly on survey design (the framing effects, etc.).

The assessment of the value of real estate from the register data is based on the average price of market transactions for different real estate types within a detailed district, which is a similar approach to that taken by the study of Johansson and Klevmarken (2007) using Swedish data.[4] The U.S. practice has been to compare survey-based wealth data that are calculated using the balance sheet principle with a register counterpart that has been indirectly calculated from income tax data using the method of capitalizing income flows (Bricker et al. 2016). However, the focus of similar analysis in the United States has been on comparing the estimate of the share of wealth held by the top 1 percent in various sources and not strictly on comparing the survey and administrative values of the same individual for all the people sampled.

3. Methodology and Estimates of Financial Fragility

3.1 Estimation Methodology

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). Following this, we show how the household probability of default is calculated on the basis of the FM and liquid assets. The probability of default is calibrated to match the aggregate household-sector ratio of nonperforming loans. Finally, a measure of banking-sector losses (loss given default, LGD) is defined, which provides an estimate of the effect 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, covering labor income, capital income, pensions, and any other public or private transfers. Income is collected for the calendar year preceding the survey (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

[4] They employ a slightly more complicated approach based on the average transaction price in a region and the tax-assessed value.

tax rates and exemptions.[5] Debt payments DP_i 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.[6] 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 C_i has been defined as the Statistics Estonia official estimate of the subsistence minimum (Statistics Estonia, table hh27 at http://www.stat.ee). The subsistence minimum without expenditures on housing was EUR 128 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 (Organisation for Economic Co-operation and Development) equivalence scale.[7] 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, Johnson, and Read 2015;

[5]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 the retired 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.

[6]Leases, credit card debt, and bank account overdrafts are excluded because the data on monthly payments for these loans are not available in the Household Finance and Consumption Survey. The exclusion of these loans should not have a major effect on the results since the majority of the loan burden in Estonia consists of mortgages, and collateralized loans make up 95 percent of the total loan burden excluding leases.

[7]The first adult household member gets a weight of 1, 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.

Ampudia, van Vlokhoven, and Zochowski 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, Hlaváč, and Jakubík 2016) or the minimum nondurable 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.

Most studies of household stress tests consider all households with a negative financial margin as distressed households and define their probability of default as 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 can avoid default. This paper applies the solvency and liquidity approach introduced by Ampudia, van Vlokhoven, and Zochowski (2016) to derive the probability of default. They show that this type of distress measure outperforms other indicators that are based on a negative financial margin or on debt-service-to-income ratio thresholds, as these tend to overestimate the exposure at default. The method used by Ampudia, van Vlokhoven, and Zochowski (2016) not only has a more realistic distress measure that employs information on income as well as on liquid assets, but also allows flexible calibration of the exposure at default ratio so that it meets the actual aggregate nonperforming loan ratio. As a result, stress tests based on microdata and macrodata can easily be compared at the same meaningful scale.

Using the idea from Ampudia, van Vlokhoven, and Zochowski (2016), we define the probability of default as follows:

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

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.[8] The very first line of the set of equations (2) shows that households with a positive financial margin will not default and their probability of default is zero. 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 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 or the share of defaulting loans in the total loan stock. Following Ampudia, van Vlokhoven, and Zochowski (2016), the formula for calculating EAD is

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

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 nonperforming loans in Estonia at the time of the survey, i.e., from March to June 2013. The survey data are used for calibration of M, and the same value of M is used for estimations based on register data. The aggregate 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 percent during the survey fieldwork period (Bank of Estonia statistics table 3.3.11). Ampudia, van Vlokhoven,

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

and Zochowski (2016) calibrate the value of M to meet the nonperforming loan ratio for the euro-area households and find M to vary a lot across countries, from 0 to 26 months.[9] Given that the share of households with a negative financial margin in the Estonian data is high compared with the actual NPL ratio (13.0 percent versus 3.4 percent; see table 1), the value of M has to be relatively low in Estonia, meaning that although the negative financial margin is frequently encountered, 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 for EAD of 3.4 percent.

Lastly, the share of banks' loan losses that are caused by defaults, or the loss given default, 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 noncollateralized loans (following the idea of Herrala and Kauko 2007 and the notation of Ampudia, van Vlokhoven, and Zacchowsky 2016):

$$LGD = \frac{\sum_{i=1}^{N} pd_i[(D_i^M - W_i^M)c_i^M + D_i^{NC}]}{\sum_{i=1}^{N} D_i}, \tag{4}$$

where LGD denotes loss given default, Di denotes debt, superscript M denotes mortgage loans, superscript NC denotes noncollateralized loans, W_i denotes assets that the bank can liquidate in the event of a default, and c_i equals one if the household is "underwater," 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 nonperforming loans.

3.2 Households' Financial Fragility Indicators: Survey Data and Historical Aggregates

Table 1 reports descriptive statistics for the financial fragility indicators from the survey: the share of households with a negative

[9] Their study covers the households of the 15 euro-area countries that participated in the first wave of the Household Finance and Consumption Survey, these being all the euro-area member states in 2010 except Ireland.

Table 1. Indicators of the Financial Fragility of Households and Estimated Loan Losses for Banks: Survey Data and Historical Aggregates

	Aggregate Historical Measures[a]	Survey-Based Estimates
Negative Financial Margin, %	—	13.0
Probability of Default, %	—	5.2
Exposure at Default, %	3.4	3.4
Mortgages, %	2.8	3.2
Noncollateralized Loans, %	6.4	8.8
Exposure at Default, Mln. EUR	230.7	165.9
Mortages, Mln. EUR	163.0	147.4
Noncollateralized Loans, Mln. EUR	67.2	18.5
Loss Given Default, %	0.8	0.4
Mortgages, %	0.5	0.0
Noncollateralized Loans, %	2.5	8.8
Loss Given Default, Mln. EUR	55.5	20.6
Mortgages, Mln. EUR	29.8	2.1
Noncollateralized Loans, Mln. EUR	25.8	18.5
No. of Obs.		769

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey data; the Bank Estonia statistics table 3.3.11 for the aggregate nonperforming loans; and the Bank of Estonia credit risk model for loan loss provisions.
Note: Indebted households are defined as households with collateralized debt and with consumer loans, not including leases, credit line overdrafts, and credit card debt.
[a]Exposure at default is measured as the aggregate ratio of nonperforming 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.

financial margin, the probability of default, etc. The first column presents estimates based on the aggregate historical banking-sector data from the survey period, i.e., the second quarter of 2013. The second column presents survey-based financial fragility indicators, which are calculated using the estimation methodology outlined in the previous section. As discussed above, we have calibrated our model so that the survey-based exposure at default rate meets the actual historical nonperforming loan rate, which was 3.4 percent during the survey fieldwork period. The microdata-based loss given default rate (second column in table 1) is benchmarked against the aggregate historical loan loss provision rate (first column in table 1). The historical data come from the Bank of Estonia credit risk model.

The aggregate provision rates are 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. In their internal credit risk models, banks usually use the estimate of the ready sale price of the real estate, which might be only 75 percent or 80 percent of the market value. Our definition of loss given default in the microdata is less conservative and is based on the full market value of the real estate. However, only a small number of loans have been written off in Estonia, even in the aftermath of the Great Recession, which suggests that banks have historically often been overprovisioning. These differences are evident in figure B.1 in appendix B, which illustrates the historical developments in the aggregate nonperforming loan rate, the loan loss provision rate, and the write-off rate in the household and corporate sectors.

According to the survey-based estimates presented in the second column of table 1, the share of households with a negative financial margin is 13.0 percent, which is similar in magnitude to the average figure for the euro area of 12.3 percent (Ampudia, van Vlokhoven, and Zochowski 2016).[10] This share of households with a negative financial margin corresponds to an average probability of default of 5.2 percent and exposure at default of 3.4 percent. Exposure at default is lower than the probability of default, which shows that households with a high probability of default have smaller debt stocks. This is in correspondence with the regularity that households with noncollateralized loans are usually financially more fragile. The value of loans exposed to default is EUR 165.9 million, which results in loss given default of EUR 20.6 million. The number of indebted households in the survey is 769, which corresponds to a share of indebted households of 30.5 percent.

[10]The percentage of households with a negative financial margin for the euro area is calculated using the Household Finance and Consumption Survey first-wave results and with basic consumption defined as 20 percent of the median income.

3.3 Households' Financial Fragility: Estimates Based on Survey and Register Data

This section compares the estimated financial fragility indicators that are based on the survey against the estimates based on data from administrative sources. The composite survey-based measures of household assets, liabilities, 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 in table 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, as the median yearly household disposable income is EUR 8,100 according to the survey and EUR 7,500 according to the administrative data (see appendix A). A possible reason for this difference is that the survey also covers nonreported income, at least in part. Alternatively, the difference may be caused by measurement error, i.e., income overreporting by survey participants. Lower estimated incomes for most of the percentiles from administrative sources raise the share of households with a negative financial margin and result in a higher exposure at default rate and larger losses for the banks.

The comparison of survey data with administrative records shows that low-income households overreport their incomes and high-income households underreport theirs in the Estonian Household Finance and Consumption Survey. The same pattern has also been detected in many earlier studies making such comparisons (e.g., Rodgers, Brown, and Duncan 1993; Bound et al. 1994; Pischke 1995). However, the turning point after which the survey-based estimates are below the register-based estimates for income occurs at a relatively high percentile of the income distribution in the Estonian Household Finance and Consumption Survey. Business income is underestimated in the register data, and the survey-based estimates show higher values for this income component. Since wages are the dominant form of income, however, they are the main source of the differences between the survey data and the administrative data. Notably, it is not the business income that generates a longer right-hand-side tail for the income distribution in the administrative

Table 2. Indicators of the Financial Fragility of Households and Potential Losses for Banks: Estimations Based on Survey and Administrative Sources

	Baseline from the Survey (1)	Replacing Income from Administrative Sources (2)	Replacing Debt from Administrative Sources (3)	Replacing Assets from Administrative Sources (4)	All Components from Administrative Sources (5)
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	3.9	3.4	5.9
Mortgages, %	3.2	3.5	4.1	3.1	6.0
Noncollateralized 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
Mortages, Mln. EUR	147.4	161.0	212.8	145.1	310.6
Noncollateralized 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
Noncollateralized 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
Noncollateralized Loans, Mln. EUR	18.5	25.1	7.8	19.3	25.6
No. of Obs.	769	769	944	769	944

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey and administrative data.
Note: Indebted households are defined as households with collateralized debt and with consumer loans, not including leases, credit line overdrafts, and credit card debt.

data, but the wage income. Unlike other forms of income, state pensions are underestimated in the Estonian Household Finance and Consumption Survey. This finding is also in correspondence with the results of earlier studies, which generally indicate that income from state transfers tends to be underestimated in surveys (Bound, Brown, and Mathiowetz 2001).

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 percent, indicating that the share of debt participation is underestimated in the survey. Further analysis by debt components shows that the participation in mortgages on the household main residence (HMR) is accurately predicted, while the participation in other real estate loans and consumer loans is underrepresented in the survey. The participation in these two debt types is substantially different in the survey data and the administrative data, as only 2.7 percent of households have other real estate loans according to the survey but 7.4 percent do according to the administrative data, while 13.2 percent of households have consumer loans according to the survey and 25.8 percent do according to the administrative data (see appendix A). The differences between the survey and administrative data for the median values of these debt types are not as substantial as those in the participation rates. One possible explanation for this tendency is respondent fatigue, as the data on household main residence mortgages are collected first, then the mortgages on other real estate, and then the consumer loans. An alternative possibility is response bias, as households may systematically underreport noncollateralized loans. There is also evidence from the United States that households tend to underreport the outstanding balance of consumer credit (Brown et al. 2011).

Replacing the debt items from the survey with the ones based on 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 after this replacement are higher than the results obtained with the survey-based measures.

Lastly, we replace the values of all real assets and liquid financial assets with the data from administrative sources. The probability of default declines slightly as a result, indicating that liquid assets are somewhat underreported in the survey. The estimated loss given default more than triples as a result of this replacement, which shows that the real estate values estimated from the data from administrative sources tend to be smaller than the survey-based values. Surprisingly, the mean and median values for the household main residence are higher in the survey data than in the administrative data, while the opposite holds for other real estate (see appendix A). However, as the participation rate is much higher in household main residences than in other real estate[11] and most of the outstanding mortgages are collateralized by the HMR, this component is behind the higher estimates of loss given default values based on the administrative data. 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 tendency to overestimate the value of the real estate in surveys relative to administrative data (or average transaction prices) has also been found in some previous studies (see, e.g., Kiel and Zabel 1999 and Johansson and Klevmarken 2007). However, we are not aware of previous research indicating that the bias in the valuation of HMRs is positive in the surveys, while for other real estate it is negative, as we find on the basis of the Estonian Household Finance and Consumption Survey data set.

The fifth column of table 2 replaces all the components of the financial margin with measures derived using the data from administrative sources. This replacement results in a somewhat higher

[11]Like in debt components, there is also some evidence of survey fatigue if the survey answers for other real estate items are compared with administrative data. The questions about the HMR are asked first, followed by the questions on other real estate items. It is evident that survey respondents underreport owning other real estate. The participation rate for the HMR is 76 percent in the survey and 69 percent in the administrative data, while the participation in other real estate is 32 percent in the survey and 39 percent in the administrative data.

rate for the probability of default than the survey-based estimate, together with substantially higher losses for the banks, especially from mortgage loans. The values for loss given default estimated on the basis of data from administrative sources are closer to the aggregate historical loan loss provisions reported in the first column of table 1 than the survey-based baseline measures are. This indicates that the estimates of real estate values by the commercial banks are closer to the transaction prices from the register than to the self-estimation by households in the survey.

Our estimates show that the financial distress indicators based on survey data were lower than the measures based on administrative sources. This implies that if countries use different methods for collecting data, some using household interviews and others using registers, it can undermine the comparability of the results. As most similar studies use data from household interviews, it is likely that the level of household distress has in general been underestimated. The comparison of the survey and administrative data from Estonia indicates that households tend to overreport their incomes and the values of their HMRs and at the same time tend to underreport the outstanding balance of their loans. Although the finding for incomes is not entirely backed by previous studies making similar comparisons (e.g., Pischke 1995), earlier research has also shown that real assets, and real estate in particular, tend to be overreported and liabilities underreported in surveys (Johansson and Klevmarken 2007, Brown et al. 2011). This indicates that net wealth tends to be measured with an upward bias in the surveys. Therefore, risk assessments for the household sector that are based on survey data should in general underestimate the actual level of financial fragility relative to estimations that are based on administrative records.

4. Household Stress Tests: The Effect of Shocks on Financial Fragility

This section gives an overview of the stress tests based on the survey and administrative data, presenting the results of standardized individual shocks to three variables. The standardized 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 quarterly data covering the period 2004:Q1–2013:Q2,[12] which is the period from Estonia's accession to the EU until the time of the survey fieldwork. It is assumed that shocks occur instantaneously and that there is no feedback from the financial sector to the real economy.

4.1 The Interest Rate Shock

First, we assess the effect of base interest rate shocks on the financial fragility of households and on banking-sector losses from defaulting loans. 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 noncollateralized loan payments are assumed to remain unaffected by this shock.[13] 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. It is also assumed that the base interest rate shock will affect the income earned from sight and savings accounts. However, the income from these sources is so small compared with other income sources that it has almost no effect on the financial margins of households.

As a result of increase in the base interest rate, the financial margin (FM_i) in equation (1) will decrease for an indebted household i

[12]The earlier years were excluded, as they were affected by structural changes caused by the transition from a planned economy to a market one. 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).

[13]The Household Finance and Consumption Survey does not collect information on whether noncollateralized loans have flexible or adjustable interest rates, but it is known that most of these loans have fixed interest rates in Estonia. As much as 67 percent 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 Household Finance and Consumption Survey (Bank of Estonia internal statistics from the Financial Stability Department). So the actual share of fixed interest rate loans among noncollateralized debt is even higher in the Household Finance and Consumption Survey data. Therefore we assume that interest rate shocks do not affect the servicing costs for noncollateralized loans, i.e., there is no pass-through of the base interest rate shock to noncollateralized loans.

because the increase in debt servicing costs (DP_i) is larger than the increase in disposable income (Y_i). A lower financial margin in turn leads to a higher probability of default depicted by equation (2) and consequently to a larger amount of loans being exposed at default (equation (3)) and higher loan losses given default (equation (4)).

The share of adjustable interest rate mortgages is 82 percent of the total mortgage stock in the Estonian Household Finance and Consumption Survey. This puts Estonia together with Luxembourg, Malta, the Netherlands, Portugal, Slovenia, and Spain in the group of countries with a relatively high share of adjustable-rate loans in the euro area (see Ampudia, van Vlokhoven, and Zochowski 2014 for estimates for the other euro-area countries). Consequently, the pass-through of this shock to the financial margin is relatively strong in Estonia.

The most common base interest rate in Estonia is the six-month EURIBOR. As much as 95 percent of all mortgage loans with adjustable interest rates are tied to this base rate in the Estonian Household Finance and Consumption Survey. 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 percent at the time of the survey and its standard deviation for the post-EU-accession period was 1.413 percent. This means that shocks of one, two, and three standard deviations correspond to rises in the EURIBOR rate from 0.318 percent to 1.1731 percent, 3.144 percent, and 4.557 percent, respectively. Although a shock as large as three standard deviations should capture extreme developments, the highest shocked value of 4.557 percent is still 0.5 percentage point smaller than the highest value seen in the sample period, which was 5.176 percent in the second quarter of 2008. This indicates that the variation in the EURIBOR rate has been quite low.

The results of the shock to the EURIBOR rate are presented in table 3. For comparative purposes, we present the stress-testing results using the survey data and the register data. Shocks of one, two, and three standard deviations increase the share of households with a negative financial margin by about the same magnitude,

Table 3. The Effect of a Shock to the EURIBOR Interest Rate on the Financial Fragility of Households

	Survey Data				Register Data			
	Pre-stress, EURIBOR = 0.318%	**1 sd Shock, EURIBOR = 1.731%**	**2 sd Shock, EURIBOR = 3.144%**	**3 sd Shock, EURIBOR = 4.557%**	**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	15.6	17.0	17.7	18.8
Probability of Default, %	5.2	5.9	6.1	6.4	6.4	6.7	7.2	7.7
Exposure at Default, %	3.4	4.9	5.3	5.9	5.9	6.3	7.2	8.1
Mortgages, %	3.2	4.8	5.1	5.8	6.0	6.4	7.3	8.2
Noncollateralized Loans, %	8.8	8.8	8.8	8.8	5.0	5.1	5.3	5.8
Exposure at Default, Mln. EUR	165.9	240.6	258.3	289.7	336.2	355.2	407.1	456.4
Mortages, Mln. EUR	147.4	222.2	239.8	271.2	310.6	329.4	380.0	426.9
Noncollateralized Loans, Mln. EUR	18.5	18.5	18.5	18.5	25.6	25.7	27.1	29.5
Loss Given Default, %	0.4	0.4	0.4	0.4	1.1	1.1	1.2	1.4
Mortgages, %	0.0	0.0	0.0	0.1	0.7	0.7	0.8	1.0
Noncollateralized Loans, %	8.8	8.8	8.8	8.8	5.0	5.1	5.3	5.8
Loss Given Default, Mln. EUR	20.6	20.6	20.6	21.1	61.5	61.7	69.1	81.7
Mortgages, Mln. EUR	2.1	2.1	2.1	2.6	35.9	36.0	41.9	52.1
Noncollateralized Loans, Mln. EUR	18.5	18.5	18.5	18.5	25.6	25.7	27.1	29.5
No. of Obs.	769	769	769	769	944	944	944	944

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey data.
Note: "sd" stands for standard deviation.

irrespective of whether these estimated effects are based on survey or register data. The EURIBOR shock of three standard deviations increases the share of households with a negative financial margin by 18 percent (from 13 percent to 15.3 percent) according to the survey data and by 21 percent (from 15.6 percent to 18.8 percent) according to the register data.

Exposure at default reacts to interest rate increases substantially more strongly according to the estimates based on the survey data than it does according to the register data. In response to the shock of three standard deviations, the EAD goes up to 5.9 percent from the pre-stress level of 3.4 percent, i.e., it rises by 74 percent. By contrast, the estimate of the EAD that is based on register data goes up from the pre-stress level of 5.9 percent to 8.1 percent in response to the shock of three standard deviations, which corresponds to an increase of 37 percent. This difference in the magnitudes of reaction is partially explainable by a lower base level of the EAD in the survey data than in the register data (3.4 percent versus 5.9 percent).

There are also differences between the survey and the register data in the reaction of the LGD to the interest rate shock. The potential losses from this shock are almost negligible according to the survey data but quite substantial according to the register-based estimates. The rise in the EURIBOR of three standard deviations increases the loss given default by only 2 percent according to the survey, while the LGD rate increases by 33 percent according to the register data. These divergent results are caused by biases in the survey estimates of liabilities and assets. The share of households with negative equity is much bigger according to the register data than according to the survey because households overestimate the value of real estate and underestimate the value of liabilities in the survey (see appendix A).

4.2 The Unemployment Shock

There are various ways to estimate the effect 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 the probability of unemployment, 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, Johnson, and Read 2015; Galuščák, Hlaváč, and Jakubík 2016; Ampudia, van Vlokhoven, and Zochowski 2014; and Bańbuła et al. 2015). The last three of the papers cited 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 modeled 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 matches the size of the shock. It is also assumed that the share of economically inactive people is unaffected by the shock. So our modeling of the unemployment shock assumes that the new and higher unemployment rate is caused by the change in one labor market flow, the flow from employment to unemployment, while other labor market flows remain unaltered.

These assumptions follow the logic of any labor 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 labor 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 level 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.[14]

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 with 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 percent. 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 labor demand shock.[15]

The new household-level disposable income (Y_i) and financial margin (FM_i) are derived using equation (1), and the new values of the aggregate financial fragility indicators are calculated. This procedure is repeated 1,000 times using a Monte Carlo simulation,

[14] The marginal effects of the model are available from the authors upon request. 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.

[15] All workers who are involuntarily separated from work due to job destruction are subject to unemployment insurance in Estonia. The insurance benefit is 50 percent of the previous wage for the first three months and 40 percent 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 percent of workers who have moved from employment to unemployment within a year are registered with the unemployment insurance fund and, of these, only 50 percent receive unemployment insurance, while 25 percent receive unemployment benefit and 25 percent 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, an unemployment benefit, and a training scholarship from the unemployment insurance fund. The severance payment is not covered by the Labour Force Survey. The size of the severance payment can be up to two months' salary.

and the effect of the unemployment shock is found as the average value of financial fragility indicators from these 1,000 replications. As a result of this shock, income will decrease for households where household members have switched from employment to unemployment, and in these households the disposable income and financial margin will decrease and lead to deterioration of the loans exposed and losses given default.

The unemployment rate is 10.9 percent in the Household Finance and Consumption Survey data, which is somewhat higher than the official estimates from the Labour Force Survey, which were 10.0 percent and 8.0 percent in the first and second quarters of 2013, respectively. The standard deviation of the official seasonally adjusted rate is 3.9 percent, 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 percent, which is higher than the historical quarterly maximum since 2004 of 18.8 percent.

The effects of the unemployment shocks are presented in table 4. For comparative purposes, we first present the estimated effects that are based on survey data and then the results that are based on the register data. Shocks of one, two, and three standard deviations increase the share of households with a negative financial margin, as well as the probability of default and the exposure at default almost linearly. The share of households with a negative financial margin increases more strongly than it did in response to the interest rate shock. This shows that more households are affected by the unemployment shock. In response to the shock of three standard deviations, the share of households with a negative financial margin increases from the pre-stress level of 13 percent to 17.1 percent according to the survey data and from 15.6 percent to 21.7 percent according to the register data. The magnitude of this increase is 32 percent in the survey data and 39 percent in the register data.

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 do. In response to the shock of three standard deviations, the EAD increases by 41 percent according to the survey data or by 29 percent according to the register data. Thus register-based estimates indicate smaller

Table 4. The Effect of the Unemployment Shock on the Financial Fragility of Households

	Survey Data				Register Data			
	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%**	**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	15.6	17.3	19.5	21.4
Probability of Default, %	5.2	5.8	6.5	7.1	6.4	7.2	8.2	9.0
Exposure at Default, %	3.4	3.8	4.3	4.8	5.9	6.4	7.1	7.7
Mortgages, %	3.2	3.6	4.1	4.5	6.0	6.4	7.0	7.6
Noncollateralized Loans, %	8.8	9.4	9.9	10.5	5.0	6.2	7.3	8.3
Exposure at Default, Mln. EUR	165.9	186.0	210.3	232.9	336.2	365.2	401.0	434.8
Mortages, Mln. EUR	147.4	166.4	189.5	211.0	310.6	333.8	364.0	392.5
Noncollateralized Loans, Mln. EUR	18.5	19.6	20.8	21.9	25.6	31.4	37.0	42.3
Loss Given Default, %	0.4	0.5	0.5	0.6	1.1	1.3	1.5	1.7
Mortgages, %	0.0	0.1	0.1	0.1	0.7	0.8	0.9	1.0
Noncollateralized Loans, %	8.8	9.4	9.9	10.5	5.0	6.2	7.3	8.3
Loss Given Default, Mln. EUR	20.6	22.7	25.1	27.2	61.5	73.0	85.1	95.9
Mortgages, Mln. EUR	2.1	3.1	4.3	5.4	35.9	41.5	48.1	53.5
Noncollateralized Loans, Mln. EUR	18.5	19.6	20.8	21.9	25.6	31.4	37.0	42.3
No. of Obs.	769	769	769	769	944	944	944	944

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey data.
Note: "sd" stands for standard deviation.

sensitivity to unemployment shocks for this variable than survey-based estimates do.

At the same time, the potential losses for the banks from the unemployment shock are larger than those from the interest rate shock. The LGD rate increases by 50 percent in response to the shock of three standard deviations according to the survey data and by 55 percent according to the register data. Evidently, households that are more strongly affected by the unemployment shock have higher loan-to-value ratios than households that are affected more by the interest rate shock, which results in a larger exposure of banks to the unemployment shocks.

4.3 The Real Estate Price Shock

The real estate price shock does not affect the financial margin of households, since the financial margin 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, i.e., equations (1)–(3) will not be affected. A fall in real estate prices increases loan-to-value ratios and the number of households with negative equity. The losses given default that are calculated using equation (4) will increase because the value of assets that the bank can liquidate in the event of a default (W_i) will decrease and the number of households "underwater" (c_i) will increase.

Real estate prices have historically been very volatile in Estonia, which experienced a very strong boom-and-bust cycle in house prices, culminating before the Great Recession. House prices dropped by 50 percent 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 percent of their highest historical value at the time of the survey. 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 fall of 24.4 percent in prices. This is much higher than in other euro-area countries and is even substantially higher than in Spain, the country with the highest standard deviation in the study by Ampudia, van Vlokhoven, and Zochowski (2016), where it was 14.3 percent. Given the sizable standard deviation in Estonia, a shock of three standard deviations cannot be considered realistic. The two-standard-deviation shock of 48.8 percent 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. For comparative purposes, we first present the estimated effects that are based on survey data and then the results that are based on the register data. Although it is only the losses from mortgage loans that are affected by these shocks, they have a strong adverse effect on loan losses. Losses given default increase by almost five times (from 0.4 percent to 1.9 percent) according to the survey data and by about 220 percent (from 1.1 percent to 3.5 percent) according to the register data. There is also a strong nonlinearity in this reaction, as the reaction in losses is much stronger to larger shocks. The takeaway from this nonlinearity 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.

As a result of the shock of three standard deviations, the expected losses for banks are more than four times larger than the pre-stress level and reach EUR 92 million according to the survey data and EUR 197 million according to the register data. Although this is a strong increase from the baseline scenario, the estimated level of losses according to the survey is similar in magnitude to the aggregate quarterly profits of the banking sector, which were about EUR 90 million per quarter in 2011–13. The estimated level of losses is about twice this value in the worst-case scenario according to the register data. Thus, even in the case of an extreme decline of 73 percent in real estate prices, the estimated losses from loan defaults by the household sector are relatively easy for the commercial banks to absorb.

The comparison of the effects of the three shocks implies that interest rate shocks have the mildest effect, followed by unemployment shocks. Shocks to real estate prices do not affect the ability of households to service their loans but have the strongest effect on the estimated loan losses of the banks.

The finding that the financial fragility of households is more sensitive to unemployment shocks than to interest rate shocks is

Table 5. The Effect of the Shock to Real Estate Prices on the Financial Fragility of Households

	Survey Data				Register Data			
	Pre-stress	**1 sd Shock, Real Estate Price Decrease = 24.4%**	**2 sd Shock, Real Estate Price Decrease = 48.8%**	**3 sd Shock, Real Estate Price Decrease = 73.2%**	**Pre-stress**	**1 sd Shock, Real Estate Price Decrease = 24.4%**	**2 sd Shock, Real Estate Price Decrease = 48.8%**	**3 sd Shock, Real Estate Price Decrease = 73.2%**
Negative Financial Margin, %	13.0	13.0	13.0	13.0	15.6	15.6	15.6	15.6
Probability of Default, %	5.2	5.2	5.2	5.2	6.4	6.4	6.4	6.4
Exposure at Default, %	3.4	3.4	3.4	3.4	5.9	5.9	5.9	5.9
Mortgages, %	3.2	3.2	3.2	3.2	6.0	6.0	6.0	6.0
Noncollateralized Loans, %	8.8	8.8	8.8	8.8	5.0	5.0	5.0	5.0
Exposure at Default, Mln. EUR	165.9	165.9	165.9	165.9	336.2	336.2	336.2	336.2
Mortages, Mln. EUR	147.4	147.4	147.4	147.4	310.6	310.6	310.6	310.6
Noncollateralized Loans, Mln. EUR	18.5	18.5	18.5	18.5	25.6	25.6	25.6	25.6
Loss Given Default, %	0.4	0.6	1.1	1.9	1.1	1.4	2.1	3.5
Mortgages, %	0.0	0.3	0.8	1.6	0.7	1.1	1.8	3.3
Noncollateralized Loans, %	8.8	8.8	8.8	8.8	5.0	5.0	5.0	5.0
Loss Given Default, Mln. EUR	20.6	31.0	55.3	91.6	61.5	80.7	120.8	197.1
Mortgages, Mln. EUR	2.1	12.6	36.8	73.1	35.9	55.0	95.1	171.5
Noncollateralized Loans, Mln. EUR	18.5	18.5	18.5	18.5	25.6	25.6	25.6	25.6
No. of Obs.	769	769	769	769	944	944	944	944

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey data.
Note: "sd" stands for standard deviation.

similar to the earlier results for other Central and Eastern European countries, which also mostly indicate that unemployment rate shocks have stronger adverse effects than interest rate shocks do (see Galuščák, Hlaváč, and Jakubík 2016 and Hóllo and Papp 2007). It is in contrast with the findings for some Western European and Nordic countries, which typically show the opposite pattern (e.g., Johanssson and Persson 2006, Herrala and Kauko 2007, and Albacete and Fessler 2010). Unemployment shocks have a stronger effect on households' loan servicing ability in Central and Eastern European countries, including Estonia, because the income replacement rate for those who become unemployed is lower in this region.

However, the most harmful shock for financial stability in Estonia 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 are very sizable and have a strong effect on the value of real estate assets.

4.4 The Effect of Standardized Shocks across Households with Different Characteristics

The previous subsections describing the effect 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,[16] and household size.

[16]The household reference person is defined following the Canberra definition (United Nations Economic Commission for Europe 2011). See Meriküll and Rõõm (2016) for a description of its derivation.

Figure 1. Variation in the Probability of Default (%) across Households with Different Characteristics and in Response to Different Shocks

Source: Authors' calculations from the Estonian Household Finance and Consumption Survey data.
Notes: "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.

The financial vulnerability of households is best captured by the probability of default. Figure 1 shows the variation in the average value of the probability of default across the household characteristics listed above and for four scenarios: pre-stress, interest rate shock of one standard deviation, unemployment shock of one standard deviation, and real estate price shock of one standard deviation. Financial vulnerability is highest for low-income households but is also above average for small households, low-net-wealth households, and households with a middle-aged reference person. In general, the survey and register data point to the same groups of vulnerable households. The variation in the probability of default is strongest across income groups, ranging from 40 percent for the lowest quintile to near-zero values for the upper three quintiles.

There are also some differences between the survey and register data in the sensitivity of the probability of default to various shocks.

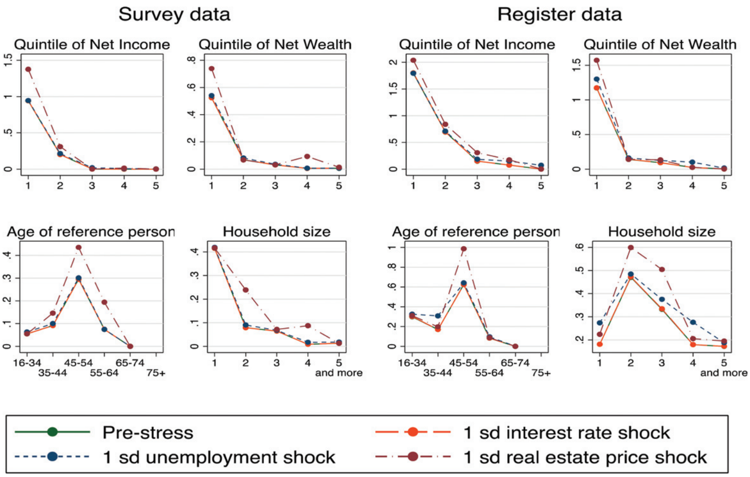
First, the household sector is relatively more vulnerable to the interest rate shock according to the survey and relatively more vulnerable to the unemployment rate shock according to the register. The possible reason for this is that noncollateralized loans are more important in the register (see appendix A). Since these loans are unaffected by the interest rate shock, they make the register-data-based estimates less responsive to this shock. The strong responsiveness to the unemployment shock in the register data can be explained by the lower estimated income from the register (see appendix A), which makes the financial margin more sensitive to income shocks from household members becoming unemployed. The real estate price shock has no effect on the probability of default, since it does not affect the flow variables (income and expenditures) that drive the probability.

The second difference between the survey and register data is the more dispersed distribution of the probability of default across household groups in the survey than in the register. According to the survey data, the probability of default is high for the first income quintile but close to zero for the upper three quintiles. According to the register data, the default risk is also quite high in the second and third income quintiles. The probability of default is also more dispersed across the wealth quintiles according to the register data than according to the survey data.

Third, the reaction to shocks is also more concentrated according to the survey than according to the register data. The effect of the interest rate shock is clearly concentrated to households in the 45 to 54 age group in the survey, while the reaction is more equally distributed across age groups in the register. It is hard to tell why the distributions of probability of default differ like this in the survey and in the register. It may be that the survey data capture extreme values or tails of the distribution better than the register or it could be that some population groups systematically misreport in the survey.

The differences in the effect of shocks across household characteristics are more pronounced in the monetary value of loss given default than in the probability of default. Loss given default is a better characterization of the risks for lenders, as a high probability of default does not necessarily imply high risks for the financial sector if the amounts of debt involved are small. Figure 2 presents loss given default in thousands of euros per household. Loss given

Figure 2. Variation in Loss Given Default across Households with Different Characteristics and in Response to Different Shocks, in Thousands of EUR per Household



Source: Authors' calculations from the Estonian Household Finance and Consumption Survey data.
Notes: "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.

default is more concentrated in specific household groups than the probability of default is. 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 larger losses for the banking sector than the other standardized shocks do, and the effect of this shock is the strongest for households in the lowest income and net wealth quintiles.

Losses for the banks are again distributed with greater dispersion in the register than in the survey, while both of the data sources point to the same vulnerable segments of households. The results are slightly different in the survey and register across household size, as single-member households bear the largest risks for banks according to the survey and two-member households do according to the register. The two-member households apparently have negative equity much more frequently in the register than in the survey.

However, the main difference between the survey and register data in the loss given default is the size of the losses—the register data predict substantially larger losses than the survey data do. There are two main reasons for this. First, the participation in debt and the share of households with negative equity are higher according to the register data than according to the survey (see appendix A). Second, the share of households with negative net value of housing equity is larger in the register data than in the survey since households tend to overvalue their real estate holdings in the survey. The second reason has the dominant role in driving the result that losses from default are higher according to the register data. The differences in debt participation rates account for only one-fifth of the differences in losses given default, while the majority of differences are caused by the share of households with negative equity being larger in the register data.

5. Conclusion

This paper assesses the financial fragility of the household sector using data for the same individuals from household interviews and administrative registers. We employ a set of stress-testing exercises in which the probability of default on loans is evaluated on the basis of households' financial margins and net liquid financial assets. The analysis employs microlevel data from the Estonian Household Finance and Consumption Survey.

The comparison of the survey and administrative data from Estonia indicates that households tend to overreport their incomes and the values of their real estate and at the same time tend to underreport their outstanding balance of loans in surveys. Although the finding for incomes is mostly not backed by previous studies making similar comparisons, earlier research has also shown that real assets tend to be overreported and liabilities underreported in surveys. This implies that net wealth tends to be measured with an upward bias in surveys. Therefore, risk assessments for the household sector that are based on the survey data are likely to underestimate the level of financial fragility, relative to estimations that are based on administrative records.

We assessed the financial risks of the household sector using three indicators: households' probability of default, exposure of loans to default, and banking-sector loan losses from defaulting household loans. Because of the biases described in the previous paragraph, the estimated financial fragility indicators tended to be lower when the estimates were based on the survey data, relative to the estimates based on the administrative data. These differences were more substantial for banks' losses given default than for households' probability of default. The probable reason for this is that the income estimates from the survey and register data are more similar than the estimates of assets and liabilities are.

After the assessment of the financial fragility indicators, we performed stress tests to evaluate how sensitive the financial vulnerability of the household sector is to adverse shocks. The stress-test elasticities of household default rates and banking-sector loan losses were assessed separately for three standardized negative macroeconomic shocks: a rise in interest rates, an increase in the unemployment rate, and a fall in real estate prices. The comparison of the effects of these three shocks implies that interest rate shocks have the mildest effect, followed by the unemployment shocks. Shocks to real estate prices do not affect the ability of households to service their loans, but they have the strongest effects on the estimated loan losses of the banks.

The finding that the financial fragility of households is more sensitive to unemployment shocks than to interest rate shocks in Estonia is similar to the earlier results for other Central and Eastern European countries, which also mostly indicate that unemployment rate shocks have stronger adverse effects than interest rate shocks do (e.g., Galuščák, Hlaváč, and Jakubík 2016, Hóllo and Papp 2007). It is in contrast with the findings for some Western European and Nordic countries, which typically show the opposite pattern (e.g., Johanssson and Persson 2006, Herrala and Kauko 2007, and Albacete and Fessler 2010). Unemployment shocks have a stronger effect on the ability of households to service their loans in Central and Eastern European countries, including Estonia, because the income replacement rate for people who become unemployed is lower in this region.

The most harmful shock for financial stability in Estonia 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 during the boom years preceding the Great Recession and the historically volatile real estate prices, so that the loan-to-value ratios of mortgage loans were high in the survey year of 2013 and the simulated shocks of one, two, and three standard deviations had a strong negative effect on the value of real estate assets.

The stress-testing exercises were performed separately on the survey data and on the register data. The effect of the adverse shocks using the survey data was similar in percentage terms to that based on the register data. However, since the pre-stress level of households' financial fragility was larger according to the register data, the resulting effects on the levels of financial indicators from the shocks were substantially larger in the register data. This applies especially to losses given default, which were up to four times larger according to the register data than according to the survey data. This result questions the comparability of stress-testing results from survey and administrative data and implies that the risks to the banking sector may be underestimated if the assessments are based on household surveys.

Next, we studied the heterogeneity in households' financial fragility. This was done by grouping households on the basis of different characteristics and evaluating the financial fragility indicators and reaction to shocks across these household groups. The households were grouped by four characteristics: net income, net wealth, age of the household reference person, and household size. Financial vulnerability varied the most across income quintiles, and was the highest for low-income households. The probability of default ranged from 40 percent for the lowest quintile to near-zero values for the upper quintiles. A similar pattern could be observed for loss given default, which was substantial for the lowest income quintile and fell to almost zero level for the upper three quintiles. The sensitivity to shocks in the case of loss given default was also the highest for low-income and low-net-wealth households. This implies that most of the financial risks from household loans are borne by low-income households in Estonia.

The heterogeneity in the financial vulnerability indicators of households was studied separately using the survey data and register data. In general, the survey and the register data pointed to the same groups of vulnerable households, as both data sources indicated that low-income households were the most vulnerable. The distribution of risks tended to be more concentrated to low-income and low-net-wealth households according to the survey data than according to the register data, but these differences in concentration were relatively small.

The stress-testing framework used in this paper can be extended to assess the effect 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 Household Finance and Consumption Survey data. It will be possible to employ either the future waves of the survey data, which will be collected at three-year intervals, or simulated data, which can be compiled with a higher frequency. Another avenue for further research is to perform stress tests on survey and administrative data for other countries too. It is important to understand differences in these data sources, as there is an increasing tendency to use administrative data for assessing financial risks.

Appendix A. Descriptive Statistics: Survey Data and Register Data

Table A.1. Descriptive Statistics: Survey Data and Register Data

	Obs.	Share in Population	Min.	P5	P25	P50	P75	P95	Max.	Mean	Total (Mln. EUR)
Assets											
Value of Household's Main Residence (HMR)											
Survey	1,778	0.765	200	4,908	21,148	44,850	75,386	200,000	1,405,385	69,152	30,240
Register	1,636	0.693	1,946	7,223	18,183	39,976	62,631	144,139	546,449	50,614	20,049
Value of Other Real Estate Property											
Survey	834	0.320	1	1,529	9,913	27,197	60,000	200,000	1,105,264	57,434	10,514
Register	1,011	0.394	13	3,054	16,133	36,293	77,183	222,743	1,932,445	69,217	15,589
Total Value of Real Estate Property											
Survey	1,870	0.805	200	5,000	25,000	50,048	100,000	289,343	1,586,472	88,480	40,754
Register	1,803	0.767	371	8,014	23,912	49,462	96,380	242,998	2,364,311	81,206	35,638
Net Liquid Assets											
Survey	2,220	1.000	0	0	60	1,162	6,152	35,420	1,240,302	8,826	5,047
Register	2,220	1.000	0	0	20	1,250	7,191	38,315	3,956,984	10,535	6,024
Liabilities											
Outstanding Balance of HMR Mortgages											
Survey	509	0.187	260	2,092	10,000	27,623	53,500	111,800	300,000	39,002	4,164
Register	476	0.177	276	2,220	12,059	28,150	55,248	116,272	295,999	40,042	4,060
Outstanding Balance of Other Mortgages											
Survey	79	0.027	100	809	8,080	21,758	52,000	92,000	170,000	32,140	501
Register	202	0.074	116	2,102	7,446	16,680	33,319	82,537	166,887	25,509	1,075
Outstanding Balance of Noncollateralized Loans											
Survey	299	0.132	9	122	600	1,396	3,317	8,600	56,000	2,768	209
Register	634	0.258	0	135	839	1,786	4,055	10,469	58,987	3,444	508

(continued)

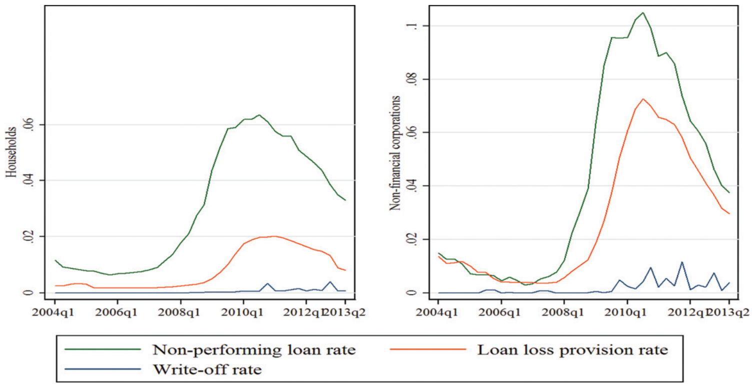
Table A.1. (Continued)

	Obs.	Share in Population	Min.	P5	P25	P50	P75	P95	Max.	Mean	Total (Mln. EUR)
Total Outstanding Balance of Mortgages and Noncollateralized Loans											
Survey	769	0.305	10	400	2,449	12,000	40,500	100,000	300,000	27,960	4,875
Register	944	0.371	65	465	2,525	10,469	36,543	102,600	321,263	26,671	5,665
Negative Equity ($(D_i^M - W_i^M) c_i^M i$ in Equation (1))											
Survey	29	0.010	612	923	4,883	8,123	23,209	76,106	104,032	19,004	111
Register	132	0.047	13	714	6,543	13,757	26,795	90,437	200,210	24,622	662
Total Household Disposable Income											
Survey	2,196	0.982	145	2,336	4,045	8,073	14,901	30,873	363,110	11,690	6,567
Register	2,131	0.941	–19,163	1,828	3,742	7,465	13,857	30,147	9,262,065	12,721	6,844
Debt Servicing Costs											
Payments for HMR Mortgages											
Survey	509	0.187	0	72	135	210	320	650	2,900	273	29
Register	476	0.177	26	75	128	209	354	708	2,823	278	28
Payments for Other Property Mortgages											
Survey	79	0.027	7	50	111	198	292	555	958	223	3
Register	202	0.074	19	55	104	153	266	519	19,243	350	15
Payments for Noncollateralized Debt											
Survey	299	0.132	0	8	38	68	123	329	1,403	107	8
Register	634	0.258	3	17	43	75	137	276	468	102	14
Payments for Household's Total Debt											
Survey	769	0.305	0	22	95	180	300	604	2,900	233	41
Register	944	0.371	7	31	93	174	319	643	19,243	266	56
Financial Margin (See Equation (1)), Monthly											
Survey	769	0.305	–1,984	–167	227	652	1,247	2,663	11,672	902	157
Register	944	0.371	–17,798	–319	165	580	1,108	2,464	14,232	779	166

Sources: Authors' calculations from Estonian Household Finance and Consumption Survey and administrative data.

Appendix B. Trends in Loan Quality and Banking-Sector Losses in Estonia

Figure B.1. Nonperforming Loan Rates, Loan Loss Provision Rates, and Write-off Rates, 2004:Q1–2013:Q2



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

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