Risk-Bearing Capacity of Households – Linking Micro-Level Data to the Macroprudential Toolkit

This paper aims to enhance the macroprudential risk assessment of households by integrating micro-level data, namely data from the Household Finance and Consumption Survey (HFCS), into the assessment. As opposed to data reported under the supervisory framework, HFCS data include detailed information on the debt and wealth of Austrian households. This paper outlines three examples of how HFCS data can improve the macroprudential toolkit.

(1) We improve the credit risk parameters in retail models used in OeNB macroeconomic stress tests by incorporating household vulnerability simulations. Vulnerability is modeled based on a combination of four macroeconomic shocks (changes in the unemployment rate, changes in income, changes in short- and long-term interest rates and appreciations of foreign currencies). In the most severe stress scenario, the probability of default (PD) of performing household exposures increases by 2.3 percentage points. (2) We analyze the debt-to-income (D/I) ratio of foreign currency debt holders as a measure of risk-bearing capacity and find that D/I ratios are unevenly distributed among these households. About 20% of foreign currency debt holders have a rather poor risk-bearing capacity in terms of income reserves and carry more than 80% of the loss potential of Swiss franc-denominated loans. (3) We use the HFCS data's singular quality of allowing the calculation and presentation of initial and current loan-to-value (LTV) ratios to show that initial LTV ratios have a positive relation with debt service-to-income ratios and with the term of a loan, but a negative relation with income.

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The financial and economic crisis that started in summer 2007 has shown that macroprudential supervision and regulation need to be significantly expanded. As a consequence, national and supranational authorities have reinforced their efforts in macroprudential supervision. However, considerable gaps remain in the analytical underpinnings of macroprudential supervision and regulation (see ECB, 2012).

In Austria, for instance, supervisory data reported by banks fail to capture the risk-bearing capacity of households and, as a consequence, of the banking system, as these data lack in-depth information on mortgage and consumption loans taken out by households. Therefore, using data from the Household Finance and Consumption Survey (HFCS) in macroprudential analysis represents an opportunity for gaining a comprehensive understanding of the vulnerabilities of Austrian households and banks. Coordinated by the European Central Bank (ECB), the HFCS is the first euro area-wide household survey that covers the entire balance sheet of households. In particular, it includes detailed information on all types of assets and debt (ECB, 2013a; ECB, 2013b).

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This paper contributes to the literature by integrating two research fields: (1) the micro- (survey-) based analysis of household vulnerability on the one hand and (2) macroprudential analysis based on supervisory data on the other. As the two fields tend to use the same terminology but apply it differently, it is necessary to present the differences in terminology first (section 1). This paper aims to improve the estimation of credit risk parameters in retail models used in the OeNB's macroeconomic stress tests by including HFCS-based simulations. These simulations rest upon the scenarios defined in the stress test run under the Financial Sector Assessment Program (FSAP) conducted by the IMF in Austria in 2013 (see IMF, 2014, and Feldkircher et al., 2013). These scenarios are also presented in section 1.

In section 2 we focus on the micro side of our analysis, i.e. the modeling of household vulnerability and changes therein due to macroeconomic developments. In particular, the simulation includes the effect of four different shocks – changes in the unemployment rate, income changes, changes in short- and long-term interest rates and appreciations of foreign currencies – on households' financial margin.

Section 3 gives an overview of where HFCS data can be used for macroprudential analysis. First of all, we present the integration of micro simulation output into macroeconomic stress tests. Second, we analyze the risk-bearing capacity of foreign currency loan holders based on HFCS data. Third, we derive loan-to-value (LTV) information of mortgage holders from HFCS data. Section 4 concludes.

1 Terminology and Scenarios

In this section we introduce definitions of the basic terminology and discuss stress test scenarios.

1.1 Comparison of Basic Terminology

There are key differences in the terminology used in the supervisory framework *(SF)* and the terminology in the literature on household vulnerability *(HH)*.[2] To avoid ambiguities and misinterpretations, this section gives an overview of some widely used concepts and provides clear definitions of how technical terms (probability of default, share of exposure to vulnerable households, loss given default) are used further down.

Setting up our methodological framework, we define four sets of households that are observed in the survey. The set of all households is denoted by T. All indebted households are contained in set D. All vulnerable indebted households are in set V. And all vulnerable indebted households with debt exceeding their assets are in set A. Thus, $A \subseteq V \subseteq D \subseteq T$.

First we need a concept to measure the vulnerability of households. The standard in the literature is a probabilistic framework (e.g. probability of default, *PD).* In the HH framework, the following binary classification is used. *PD(HH)* can be defined as follows: $PD_i = 1$ if household i is classified as vulnerable.[3] These households are summarized in set V. For all indebted households that are not in V, $PD_i = 0$.

In the supervisory framework, the *PD* of a household refers to the probability that a household defaults within one year. A loan is defaulted if one of the default criteria under Basel II are met: full repayment unlikely and/or

interest or principal payments on a material exposure more than 90 days past due. If $PD_i = 1$, the household has already defaulted. For nondefaulted households the PD lies in the open interval $(0,1)$ and is assigned to all households in set D.

In the literature on household vulnerability, exposure at risk is a very important term. It gives an estimate of the aggregate level of household liabilities that may turn into loans that cannot be repaid. However, to avoid any mix-up with the supervisory term "exposure at default" we introduce a different term: share of exposure to vulnerable households (SEvH),

$$SEvH = \frac{\sum_{i \in V} Debt_i}{\sum_{i \in D} Total\ Debt_i}.$$

In the supervisory context, loans belonging to the *SEvH* will most likely be classified in the bad rating categories (i.e. have high *PDs)* of banks.

Finally, the micro data-based literature on vulnerable households defines loss given default (LGD) as follows: For all households i in set A the following ratio is calculated to approximate the losses of banks caused by vulnerable households:[4]

$$LGD = \frac{\sum_{i \in A} \left(Debt_i - Assets_i \right)}{\sum_{i \in D} Total\ Debt_i}$$

The LGD in the supervisory context specifies the proportion of a loan expo-sure that will be lost (i.e. will not be recoverable) under the assumption that the borrower defaults. The *LGD* represents a credit risk parameter that is used for determining a bank's capital requirement under the internal ratings-based (IRB) approach of Basel II.

1.2 Scenarios

The input for the different scenarios in the stress testing exercise is a combination of international benchmarks and the OeNB forecasting model. We take the following real-world example from previous rounds of stress tests in Austria (table 1) to achieve a clear understanding of the differences in the use of information at the micro level. All the scenarios are hypothetical and no probabilities are attached to the changes of each indicator.

The various scenarios are based on different time frames. For scenarios 1 and 2 (which were used in the FSAP in 2013) the last observed data are from the fourth quarter of 2012, so the first and second years of the scenario refer to 2013–2014. We include scenario 3 in order to see the changes resulting from a more severe recession given by a larger assumed reduction of GDP. This scenario is based on the assumptions of the macro stress testing model in 2010, so that the last observed data are from the fourth quarter of 2009, and the first and second year changes refer to 2010 and 2011.[5]

In the baseline scenario (scenario 1), the GDP growth rate in year one is assumed to be 1.1% and increases in

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[4] *Depending on which assets are taken into account, one can define alternative LGD measures. In addition to the LGD measure presented here (where all assets of each household are taken into account), for the micro simulations below we additionally use an alternative LGD measure that only takes into account housing wealth:*

$$LGD = \frac{\sum_{i \in A} Debt_i - Housing\ wealth_i}{\sum_{i \in D} Total\ Debt_i}$$

[5] *The forecast path of the exchange rate does not change from scenario 2 to scenario 3 since the scenario at the time it was used in the stress test model in 2010 did not include the modeling of exchange rate developments. Here we use the development shown in scenario 2.*

Scenarios for Changes in Households' Vulnerability

	GDP	URX	PYR	STIR	LTIR	EX SFr	EX JPY
	Annual growth rates in %						
Scenario 1: baseline							
First year	1.1	2.5	1.9	41.1	18.4	0.0	0.0
Second year	2.0	−0.1	1.3	86.5	15.6	0.0	0.0
Scenario 2: stress scenario I							
First year	−0.8	7.5	1.6	304.2	23.1	−7.9	−17.4
Second year	1.1	4.0	1.3	30.2	15.0	−3.4	−7.6
Scenario 3: stress scenario II							
First year	−2.7	7.9	−2.3	57.7	10.7	−7.9	−17.4
Second year	0.2	12.1	1.6	45.5	6.8	−3.4	−7.6

Source: OeNB.

Note: This table shows the growth rates of specific indicators in various scenarios used in stress tests. The columns display the growth rates of GDP (real), the unemployment rate (URX), private sector disposable income (PYR), short- and long-term nominal interest rates (STIR and LTIR, respectively) and the euro exchange rates against the Swiss franc (EX SFr) and the Japanese yen (EX JPY).

the following year to 2%. Exchange rates are assumed to stay the same. Unemployment (URX) increases in the first year and decreases slightly afterwards, disposable income of the household sector increases slightly and interest rates increase strongly. This scenario provides the most optimistic path of the economy among the three scenarios displayed in table 1. Scenario 2 provides a mild stress scenario. Scenario 3 defines a severe but plausible stress scenario, which is comparable to the economic downturn in Austria in 2009. Note that in scenarios 2 and 3, we assume that the exchange rates of the euro against the Swiss franc (EX SFr) and the Japanese yen (EX JPY) decrease.

Furthermore, the increase in disposable income (PYR) is slower in scenario 2 compared to scenario 1; disposable income decreases in year one in the most pessimistic scenario (3). The increase of short- and long-term interest rates (LTIR) is more severe in scenario 2 than in scenario 3. However, the absolute interest rate level is higher in scenario 3 than in scenario 2 due to a lower observed starting level for the simulation forecast.

2 Modeling Household Vulnerability at the Micro Level

The following section lays out in detail the set-up of the micro-level simulation of households. Starting with some information on the literature, we explain the methodology, introduce the underlying data and finally discuss the output.

2.1 Literature

An overview of the literature focusing on econometric analyses documenting household debt and vulnerabilities at the micro level is provided by Albacete and Lindner (2013) and Albacete and Fessler (2010). Most of these studies[6] concentrate on the discussion and identification of weaknesses of households alone, without establishing a specific connection with the work of macro

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[6] *See e.g. Costa and Farinha (2012) for Portugal. The most recent articles, which are not included in the literature survey in Albacete and Lindner (2013) due to their late publication date, i.e. Hlaváč (2013) for the Czech Republic and Bilston and Rodgers (2013) for Australia, are no exception.*

models or other sectors of the economy. One noticeable exception is Andersen et al. (2008), who elaborate a potential set-up for the integration of micro-level information into the macro stress testing model. On the household side they use – similar to the approach in this paper – information from macro-model forecasts together with micro-level information (survey and register data) for households in order to estimate the rate of vulnerable households and debt at risk, which feed back into the banking model.[7] In what follows we propose a methodology for using available micro-level information for macro stress testing models in macroprudential analyses for Austria.

2.2 Methodology

Following Albacete and Fessler (2010), we define the financial margin FM_i of a household i as

$$FM_i = Y_i - BC_i - DS_i \qquad (1)$$

where Y_i is disposable household income, BC_i is basic consumption and DS_i is debt service. Financial margins are therefore a continuous measure of how well a household is able to make ends meet.

In order to focus on potentially vulnerable households and to see whether they can pose a threat to the stability of the Austrian financial market, we define a household as vulnerable if it has a negative financial margin ($FM_i < 0$) and as not vulnerable otherwise ($FM_i \geq 0$). The probability of default PD_i is then defined as:

$$PD_i = \begin{cases} 1 & if \ FM_i < 0 \\ 0 & if \ FM_i \geq 0 \end{cases}$$

Thus, PD_i is a binary variable that can take only the values 0 or 1 and, therefore, in our model the percentage of vulnerable households equals the mean probability of default, which is the key measure to monitor the resilience of households under different shocks.

Four types of shocks are modeled: changes in the unemployment rate, income changes, changes in the short-term and long-term interest rates and appreciations of foreign currencies.

The unemployment shock is simulated using the same model as Albacete and Fessler (2010). We use a method that ensures that those employed individuals that have a higher probability of becoming unemployed have a higher chance of being drawn into the sample of newly unemployed individuals than those with a lower unemployment probability (for details, see Albacete and Fessler, 2010). An employment shock results in a decrease of disposable income (Y_i in equation (1)) and, consequently, of the financial margins of the household hit by the shock.

The income shock is modeled via a reduction of income of all households (Y_i in equation (1)). Unlike the unemployment shock, the income reduction affects all households equally. We use this shock to cover the change in the macro indicator disposable income of the household sector used in the macro stress test model.

The interest rate shock is modeled by an adjustment of the household's debt service (DS_i in equation (1)). A household's debt service consists of two parts, amortization and interest payments. Obviously, interest payments are the part affected by an interest rate rise. We further distinguish between

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[7] Andersen et al. (2008) also model micro-level estimations for the corporate and banking sectors, which are not discussed in the paper at hand since the quality of existing procedures is already more advanced and we focus solely on the integration of household-level information into the macro model in Austria.

short-term and long-term interest rates, assuming that a rise in the short-term interest rate will only affect loans with variable interest rates, while a rise in the long-term interest rate is going to affect every loan type.

Finally, the exchange rate shock is also modeled by a change of the household's debt service given that the household has a foreign currency loan. But this time, both parts of the debt service are affected by the appreciation of the foreign currency: First, amortization increases as the outstanding amount in euro has suddenly risen (everything else staying constant); and second, as a consequence of the rise of the outstanding amount, interest payments also increase.

These shocks and the scenarios laid out in section 1.2 are modeled at the micro level. To use the results of this analysis for comprehensive scenario analyses in the macro model we have to combine the shocks of all the components of the financial margin and observe the resulting changes in households' vulnerability. We model these combined shocks by assuming that the shocks are independent from each other; therefore we look at the change in the financial margin resulting from the sum of each one of the four shocks described above. In an unstable economic environment households that are exposed to various shocks are the ones which are hit hardest. This is captured by the combination of the shocks that are modeled.

2.3 Data and Definitions

The data for this micro-level analysis were taken from the Austrian HFCS's 2010 wave. At the Eurosystem level, the HFCS is coordinated by the ECB;[8] the OeNB is responsible for conducting the survey in Austria. HFCS data provide detailed information on the whole balance sheet as well as several socio-economic and sociodemographic characteristics of households in the euro area.[9] Additionally, some specific variables for Austria which are not publicly available were used in this study (e.g. information on foreign currency loan holders).

The results reported in the present paper pertain to households in Austria only. All estimates are calculated using the final household weights and the survey's multiple imputations provided by the data producer (see Albacete et al., 2012b, for a detailed description of the survey methodology).

We calculate each household's financial margin as follows: For Y_i and BC_i, we use total monthly net income and total monthly consumption (without rent,[10] taxes and durable goods) as recorded by the household. For DS_i we use the sum of payments for mortgages (mortgages on the main residence and on other real estate properties) and payments for noncollateralized loans.[11]

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[8] The HFCS is envisaged to be conducted about every three years. Hence, an update of the data underlying the micro-level model of household vulnerabilities could be carried out. The HFCS in Austria has no panel component.

[9] In the first wave of the HFCS, 15 out of the 17 euro area countries at the time of the field period collected the data. Estonia and Ireland will be included in the second wave.

[10] Rents are not part of basic consumption due to data limitations. We only know how much rent is paid by renters, but do not know how much homeowners spend on utilities (e.g. electricity and gas). Hence, we decided to leave out expenditure on rent and utilities from the definition of basic consumption. However, as we are mainly interested in changes of the probability of default and not in its absolute values after the changes, this data limitation should not be problematic.

[11] Leasing payments are excluded.

Furthermore, we define the household's debt stock as the sum of the outstanding balance of mortgage debt and the outstanding balance of nonmortgage debt (including credit line/overdraft, credit card debt above the monthly repayment and noncollateralized loans). Finally, gross wealth is defined as the sum of total real assets (main residence, other real estate property, vehicles, valuables, and self-employment businesses) and total financial assets (deposits, mutual funds, bonds, non-self-employment private businesses, publicly traded shares, managed accounts, money owed to households, voluntary pension/whole life insurance and other financial assets).

There is a total of 2,380 households in the net sample of the HFCS in Austria. According to the definition above, about 64% of the household population[12] do not hold debt, 3% hold debt and are vulnerable and 33% hold debt but are not vulnerable. Among those holding debt, 40% hold only mortgage debt, 48% hold only nonmortgage debt and 12% hold both types of debt. For the analysis, we focus only on indebted households, as it is evident that households without debt cannot pose a threat to the stability of the Austrian financial market.

We empirically implement the shocks as follows: For the unemployment shock we model unemployment for the household's reference person and assume – for reasons of simplicity – that the other working persons in the same household cannot become unemployed. Each reference person's probability of becoming unemployed is predicted using a logit model which includes as regressors characteristics of the reference person (age, education and gender) and household characteristics (income, total number of members, number of members in employment, number of members aged 18 and over, number of members aged 65 and over and region). The decrease of disposable household income after the shock is estimated by subtracting 45% of the reference person's net wage[13] from total household income, which corresponds to the unemployment benefits according to the current Austrian unemployment benefit rules (see e.g. BMASK, 2012). We repeat the unemployment shock 1,000 times using a Monte Carlo simulation, calculate PD and LGD each time and finally take the mean of each one of these indicators over all simulated draws.

For the interest and exchange rate shocks we need to estimate the changes in debt service after the interest rate variation and after changes in exchange rates. Therefore, we use HFCS information on the characteristics of credit contracts. In the case of bullet loans, for example, the shock transmission is relatively simple because debt service only consists of interest payments, while amortization is zero. In such cases, debt service R is estimated by $R = S_{t-1} \cdot i$, where S_{t-1} is the amount still owed (which changes in the exchange rate shock[14]) and i is the interest rate (which changes in the interest rate

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[12] *According to the survey literature, one has to apply household weights to estimate population parameters. This has been done in the figures provided, so that a share of 64% of the household population in Austria that are not indebted does not necessarily require 64% of households in the sample not to have debts.*

[13] *The reference person's net wage is estimated by dividing net household income by the number of household members in employment because net income is not available at the person level.*

[14] *For reasons of simplicity, it is assumed that the exchange rate changes of the Japanese yen are equal to the exchange rate changes of the Swiss franc. This assumption is justified by the fact that the vast majority of all foreign currency loans in Austria is held in Swiss francs. According to the HFCS, 93% of all foreign currency loans that are a household's highest mortgage on its main residence are denominated in Swiss francs.*

shock). In the case of loans other than bullet loans, debt service (interest payment and amortization) is estimated by

$$R = S_{t-1} \cdot \frac{i \cdot (1+i)^{n-t}}{(1+i)^{n-t} - 1} \ ,$$

where n is the term of the loan and t is the time elapsed since the loan was taken out.[15] The change in the debt service of an indebted household due to a shock is estimated by the percentage change of the calculated debt service (debt service after the shock divided by debt service before the shock). This percentage changes are applied to the debt payment recorded by the household in order to calculate the absolute value of the household's debt service after the shock.

Finally, we implement the income shock simply as a relative change of net household income for all households.

2.4 Micro-Simulation Output

In order to understand the complete picture of households' liabilities in Austria one needs to estimate and assess the level as well as the distribution of debt and vulnerabilities before looking at the micro simulation investigating stress scenarios for households. The main indicators derived from the first wave of the HFCS 2010 are published and discussed in Albacete and Lindner (2013) and are therefore not described here.

Table 2 shows the results of the micro simulation of the stress scenarios described above. The PD and two LGD measures are split into mortgage

Table 2

Micro Simulation of Stress Scenarios Using HFCS Data

	PD (HH)[1]			LGD (HH)[2]			LGD2 (HH)[3]		
	All debt holders	Mortgage debt holders	Non-mortgage debt holders	All debt holders	Mortgage debt holders	Non-mortgage debt holders	All debt holders	Mortgage debt holders	Non-mortgage debt holders
%									
Current situation									
	8.99	12.71	7.39	3.60	3.57	11.42	4.98	4.94	18.61
Scenario 1: baseline									
First year	9.32	13.27	7.80	4.21	4.28	11.45	5.61	5.66	18.64
Second year	9.21	13.08	7.77	4.21	4.28	11.42	5.60	5.66	18.61
Scenario 2: stress scenario I									
First year	9.58	13.72	7.85	4.24	4.30	11.45	5.63	5.69	18.66
Second year	9.46	13.45	7.88	4.23	4.30	11.45	5.63	5.69	18.65
Scenario 3: stress scenario II									
First year	11.23	15.40	9.47	4.29	4.30	11.86	5.70	5.69	19.10
Second year	11.49	15.76	9.78	4.31	4.30	11.93	5.72	5.69	19.21

Source: HFCS Austria 2010, OeNB.

[1] PD (HH) = share of vulnerable households as a percentage of indebted households.
[2] LGD (HH) = sum of vulnerable households' debt that is not covered by their total wealth divided by total debt of all households.
[3] LGD2 (HH) = sum of vulnerable households' debt that is not covered by their housing wealth divided by total debt of all households.

Note: The number of simulations is 1,000.

[15] There are a few cases in which not all of these parameters were available in the data, either due to nonresponse (e.g. year when the loan was taken out), the structure of the questionnaire (e.g. loan number 4 or above for each loan type) or special cases (e.g. loans without a fixed term). In all these cases the missing parameters were multiply imputed using a Bayesian approach.

and nonmortgage debt to highlight the differences between the two debt markets. We can see that, overall, the current PD of Austrian indebted households is about 9%, which is equivalent to 9% of indebted households being vulnerable according to our financial margin measure. The proportion of total debt held by vulnerable households that is not covered by these households' assets (LGD) equals 3.6% or, alternatively, about 5% when only housing wealth is taken into account. The scenario simulation shows that PD increases from 9% to up to 11.5% in the strongest scenario (stress scenario II). The increases of LGD are stronger, ranging from 3.6% to up to 4.3% (or from 5% to 5.7% according to the alternative LGD definition).[16]

Table 2 also shows that while the PD of nonmortgage debt holders is much lower than the one of mortgage debt holders, LGDs are much higher. This is because households in the mortgage debt market probably have a much higher debt service than households in the nonmortgage debt market, but at the same time they are wealthier and can provide more collateral than vulnerable households in the nonmortgage debt market.

This pattern remains the same across all stress scenarios, although the shocks have very different impacts on the two debt markets. While PD changes for mortgage debt holders are similar to PD changes for nonmortgage debt holders, LGDs change much less for households in the nonmortgage debt market than for those in the mortgage debt market. This is a clear indication that in the nonmortgage debt market new vulnerable households, i.e. house-

holds that become vulnerable by the stress simulation, tend to have lower nonmortgage debt and higher wealth than the households that are already vulnerable before the shocks.

3 Applying Micro-Level Data in Macroprudential Analysis

This section gives examples of how HFCS data can be used in macroprudential analysis. Solvency stress tests based on macroeconomic scenarios constitute an important area of application. Here, the framework presented in section 2 can be used to model domestic households' credit risk. Moreover, the data offer an opportunity to refine the sensitivity analyses used for assessing the credit risk emanating from foreign currency shocks to which domestic borrowers in foreign currency are exposed. Finally, HFCS data can be used to derive loan-to-value (LTV) information of Austrian real estate household loans.

3.1 Integration of Micro-Level Information into Solvency Stress Testing

Solvency stress tests analyzing the banking system's vulnerability to macroeconomic downturns are a key component of the OeNB's macroprudential toolkit. An essential element of a solvency stress test is the translation of the scenarios (baseline and stress) into the risk parameters PD and LGD (in the supervisory context). To that end, econometric models[17] are employed that describe how risk parameters evolve during the stress test horizon in terms of relative changes with respect to the starting point. The relative changes are then applied to banks' individual

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[16] The SEvH measure (see section 1.1), which is not displayed in the table due to space constraints, ranges from currently 22.6% to up to 27.4% in the strongest scenario.

[17] For a detailed presentation of the PD models see Kerbl and Sigmund (2011).

starting values. By applying the resulting risk parameters to the associated exposures, amounts of expected losses are derived, which finally represent banks' credit risk impairments in the scenarios (see Feldkircher et al., 2013).

The framework for modeling household vulnerability presented in section 2 can be used as an alternative to the model currently employed in the solvency stress test for generating households' PDs in the scenarios. Those variables in table 1 that serve as input to the domestic household vulnerability model are readily available as part of the stressed macro variable set. Table 2 gives the PDs (in the household vulnerability model context) under the current condition and at year-end for the different scenarios. The relative changes of these PDs can be used as a proxy for the relative changes of the PDs in the supervisory context. It has to be borne in mind, however, that changes in household vulnerability are by definition calculated for all indebted households included in the survey sample, i.e. for both households identified as being vulnerable and households without financial difficulties. In the stress testing framework, on the other hand, we are interested only in the probability that performing exposures default. Therefore, in order to apply the changes in household vulnerability to the PDs in the stress testing framework in a consistent way, we have to include also nonperforming exposures in the aggregate initial stress test PD value. This ensures that we base the PD changes on the same reference population (i.e. on performing as well as nonperforming exposures) in both, the household vulnerability and the stress testing con-

Chart 1

Path of PDs in Stress Scenario II[1]

PD in %
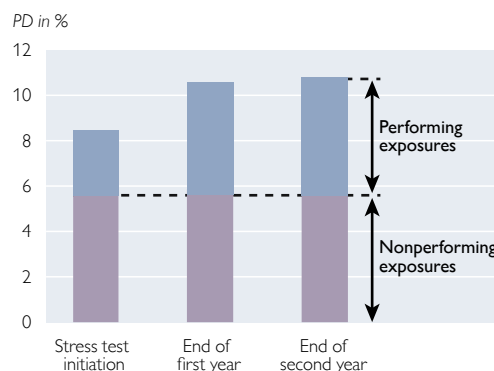
Source: OeNB.

[1] Based on the household vulnerability model, anchored at the unconsolidated average retail portfolio PD of IRB banks.

text. From the resulting stressed PDs, which again pertain to all exposures, we can finally derive the stressed PDs of the performing exposures.

In stress scenario II in table 2, for example, the household vulnerability model for all debt holders yields a relative change in PDs of 25% within the first year (28% within the first two years). Chart 1 shows the path of the resulting aggregate PDs in the supervisory context in stress scenario II.

In the chart, the aggregate PD at stress test initiation (8.4%; bar on the left) is given by the volume-weighted average of the retail portfolio PDs of those Austrian banks that use the internal ratings-based (IRB) approach.[18] It includes both performing and nonperforming rating classes. If we consider only performing rating classes, the corresponding value amounts to 2.9% (upper part of the bar on the left). The difference (5.5%; lower part of the bar on the left) is attributable to nonperforming exposures. The contribution of the initially nonperforming expo-

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[18] Data on PDs are as on December 31, 2010, in order to be consistent with the HFCS in Austria, which was conducted between Q3 2010 and Q2 2011. They are based on unconsolidated reports in order to reflect domestic customers' creditworthiness.

sures to the overall stressed PDs stays constant over the stress test horizon. Therefore the change in total PD by 25% (28%) translates into a change in the PD of the performing exposures by 73% (81%).

3.2 Foreign Currency Loans

A particularity of the Austrian financial system is the relatively high share of household loans denominated in foreign currency (see e.g. Boss, 2003; Beer et al., 2008; or Albacete et al., 2012a). The risks associated with an appreciation of the currency in which the loan is denominated – in Austria usually the Swiss franc – vis-à-vis the euro have been a cause of concern with regard to the stability of the Austrian banking system since more than a decade.[19] In the past, various supervisory measures have proved effective in substantially reducing new foreign currency lending, thus gradually reducing the overall stock of outstanding foreign currency loans.[20]

Because these legacy assets will continue to pose a challenge to the Austrian banking system they are subjected to sensitivity analyses in the framework of the OeNB's macroeconomic stress tests. The most recent test was run in the course of the IMF's FSAP in 2013 (see IMF, 2014). The sensitivity analysis was confined to Swiss franc loans because, according to supervisory data, they represent more than 90% of all foreign currency loans, which is almost identical to the equivalent estimate from the HFCS (see footnote 14 in section 2.3).

In the context of stress testing domestic foreign currency exposures, data availability is a crucial issue. Although supervisory reporting provides good data on volumes and remaining maturities of these loans at an aggregated level, information about borrowers' risk-bearing capacity is sparse. A crucial parameter in the sensitivity analysis is the ratio D/I, defined as a borrower's debt repayment obligation D within a certain period of time (e.g. one year) over her/his income within the same period after deducting debt repayment and total consumption. This ratio represents a measure of how well a borrower can cope with an appreciation of the loan currency. No explicit supervisory data on this ratio are available. So far, this parameter was set to a value that is assumed to be consistent with the supervisory requirement that foreign currency loans may only be granted to customers that can adequately cope with an appreciation of the loan currency.

In this context, HFCS data can be used to shed light not only on the magnitude of the average D/I ratio but also on its distribution across households.[21] It turns out that the majority of foreign currency borrowers (about 80%) possesses sufficient income reserves to cope even with a substantial appreciation of the Swiss franc vis-à-vis the euro (see also Albacete et al., 2012a).[22] However, about 20% of foreign currency borrowers only show a rather poor risk-bearing capacity in terms of income reserves. If these weak borrowers are concentrated at certain banks or in certain regions there may exist consid-

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[19] In the stress scenarios (see section 2 above), the impact of changes in the exchange rate is also taken into account.

[20] The stock of foreign currency loans to Austrian households amounted to EUR 29.5 billion as at end-September 2013 after having declined by 42% in foreign exchange-adjusted terms within the preceding five years (see OeNB, 2013).

[21] When the indirect credit risk of foreign currency loans is treated in a separate sensitivity analysis this has to be taken into account in the household vulnerability model of section 2 in order to avoid double counting.

[22] The appreciation of the Swiss franc vis-à-vis the euro serves as a hypothetical stress scenario. No probability is attached to this event.

Chart 2

Share of Estimated Losses across Debt Repayment Obligation-to-Income Ratio Quintiles[1]

%
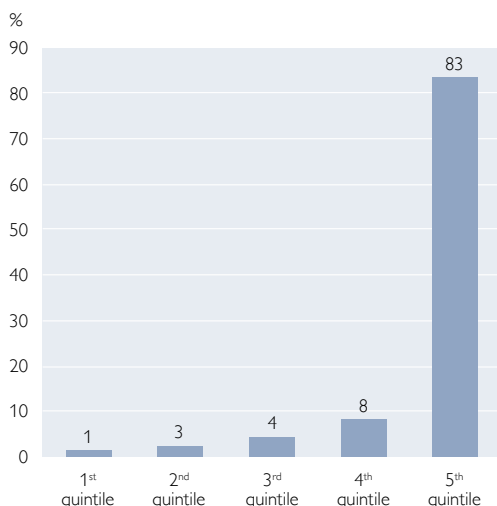
Source: OeNB.

[1] Loss estimation based on the model used in the FSAP 2013 sensitivity analysis.

erable concentration risks even when the respective loans are collateralized by real estate.

Chart 2 shows the heterogeneity of Swiss franc loan borrowers as regards their ability to cope with appreciations of the Swiss franc. We divided the borrowers covered in the HFCS into quintiles according to their risk-bearing capacity as measured by the D/I ratio. For each quintile the share of losses generated in the FSAP sensitivity analysis is shown.

Chart 2 points to the fact that — according to the model used in the FSAP 2013 sensitivity analysis — more than 80% of the loss potential of Swiss franc loans emanates from only 20% of foreign currency borrowers (located in the fifth quintile).

3.3 Loan-to-Value Ratios

A third potential field of application of micro-level information is loan-to-value (LTV) ratios. There are different loan-to-value ratios that are generally monitored. They differ in terms of their distinct purpose and sometimes also in terms of data availability. We focus on (1) *initial* and (2) *current* LTV ratios. To analyze the financial stability of an economy, both measures have to be taken into account. However, it seems obvious that they are different in terms of focus and use.

The *initial* LTV ratio is defined by the initial amount of (mortgage) debt divided by the value of the specific real estate at the time the mortgage was taken out. Although the ratio is not included in any reporting data in Austria, it should, in principle, be readily available for the creditor that grants the loan. Limits on (initial) LTV ratios are used as a macroprudential tool[23] because they can contribute to making financial institutions and households more resilient to shocks to asset prices, interest rates and income. They can be set in a time-varying manner (to mitigate procyclicality) and/or as a static cap.[24] Initial LTV limits are usually applied with a focus on a medium- to long-term stabilization of financial markets.

By contrast, the *current* LTV ratio is defined as the currently outstanding amount of (mortgage) debt divided by the current value of the specific real estate. This measure is used to analyze the financial stability of an economy at a specific point in time. The information necessary to calculate the

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[23] Asian emerging countries have set such limits in the aftermath of the 1990s Asian crisis (Hong Kong Monetary Authority, 2011). But also some European countries like Hungary, Norway and Sweden have recently adopted such credit-limiting policies (Lim et al., 2013).

[24] As house prices vary over time, caps on loan-to-income (LTI) or debt-servicing costs-to-income (DTI) may be stricter than LTV limits during phases of rising house prices.

current LTV ratio is not generally available to the financial intermediary that granted the loan (except for occasional re-evaluations) because it is not known how real estate prices evolve at the individual level. Hence, the information has to come from the debtor. Having an impact on financial stability, this indicator provides important information that can be used to inform a regulator, but – contrary to the initial LTV – it cannot be the target of specific rules.

For a full picture of LTV ratios a combination of household-level information (from the HFCS) together with data reported by monetary financial institutions would be desirable. An analysis including both sources could provide a clear understanding of both the creditor and the debtor side. So far, however, the HFCS is the only recently published source that allows an estimation of the LTV ratio of Austrian household real estate loans. The information provided by the HFCS allows the estimation of both initial and current LTV ratios. Albacete and Lindner (2013) show a cyclical pattern of median initial LTV ratios in Austria, with an upward trend since the 1990s (when LTV ratios ranged from 40% to 50%) and peaking before the beginning of the financial crisis in 2008 (60% to 65%). Since then the median LTV has fallen slightly, to below 60% in the years after 2008.[25]

Granting higher loans in relation to the value of the real estate used as collateral potentially increases the LGD for banks. Higher LTV ratios are, however, only the second line of defense for banks. Therefore, a high income buffer

is essential to absorb shocks and in that way help to prevent default in the first place. Chart 3 shows the median initial LTV ratio for debt service-to-gross income ratio[26] quintiles. From a macroprudential perspective, it is interesting that households with higher debt service-to-income ratios have higher LTV ratios.

The first quintile of the debt service-to-gross income ratio shows a median initial LTV of 32% whereas the 20% showing the highest debt service ratio have a median LTV ratio of 87%. As a consequence, a loan default is more likely for households with a lower risk-absorbing capacity due to their higher debt service ratio. However, LTV ratios are below 100% even in the fifth quintile. In line with these results, households with lower gross income

Chart 3

Median Initial LTV Ratio across Debt Service-to-Gross Income Ratio Quintiles

Initial LTV ratio in %
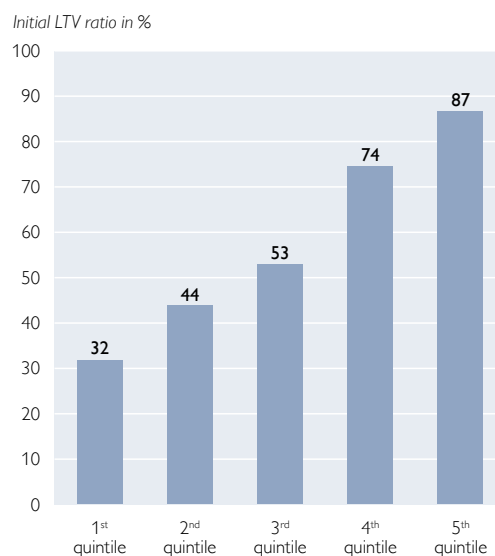
Source: OeNB.

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[25] As these are median estimates caution should be applied when comparing them with aggregate macro data, which can only provide means rather than medians.

[26] In contrast to the debt-to-income (D/I) ratio in section 3.2, the denominator here is gross income; so debt repayment and total consumption are not deducted.

(not taking into account debt service) show higher LTV ratios.

Further analyses reveal a positive relation between the term of a loan and the initial LTV ratio. Arguably, mortgage holders with higher leverage tend to opt for a longer payback period in order to limit the periodic debt service. Therefore, a LTV cap would not only affect loans with longer terms but in that way (and taking into account the results over income quintiles) would limit lending to households with a lower risk-bearing capacity. This analysis suggests that introducing and calibrating such a cap on LTV ratios is not an easy task. In order to achieve results that may feed into a targeted macroprudential policy, not only the overall LTV development but also differentiated information such as terms of loans as well as the risk-bearing capacity of households has to be considered.

4 Conclusions

This study focuses on how to use micro-level household information from the HFCS in macroprudential analysis. By integrating detailed information about the liability side of households' balance sheets into macroprudential modeling we aim at increasing our understanding of the ability of households to absorb shocks. So far, domestic households have not been a source of serious risk to the Austrian banking system. However, many examples from other countries (e.g. Spain, the U.S.A. and the U.K.) have shown that indebtedness in the household sector can give rise to problems in the financial sector; therefore a close monitoring of household indebtedness seems warranted.

We identify three possibilities for improving the macroprudential toolkit and present approaches using HFCS data.

First, building on previous work, we develop a model of household vul-

nerability. It can be used for deriving estimates of the change of default probabilities (as well as losses) in stress scenarios at the micro level. Applying these results can improve the modeling of Austrian households' credit risk in the OeNB's stress test tool ARNIE. In upcoming stress tests the household vulnerability model will replace the existing module for stressing domestic retail portfolios.

Second, we employ HFCS data to estimate the distribution of a parameter measuring the risk-bearing capacity of domestic foreign currency borrowers. It turns out that the majority of foreign currency borrowers display a high risk-bearing capacity. However, about one-fifth of them show a rather poor risk-bearing capacity in terms of income reserves, which could lead to problems if the currency in which the loan is denominated appreciates. By using HFCS information, we enhance the parameter calibration in the OeNB's sensitivity analyses for foreign currency lending. Subsequently, we will analyze whether the exchange rate effects of the macroeconomic stress scenario on foreign currency loans can be integrated into the OeNB's regular solvency stress test by means of HFCS data. This would lead to a more unified application of the stress scenario.

Third, we use HFCS data to estimate LTV ratios. This way, existing gaps in the supervisory data can be filled. Although HFCS data shed light on the debtors' side of the mortgage market, additional information about the creditors' side would be desirable.

This paper shows the potential of an integrated use of supervisory and household data. It is aimed at improving the synergies between micro-level household data analysis and macroprudential risk assessment.

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