Stress Testing Austrian Households

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Over the past decades, household debt has increased sharply, both in absolute and relative terms, in almost all OECD countries. As the U.S. subprime crisis recently showed, even a relatively small number of indebted households can produce considerable turmoil if the sustainability of their debt is in question. The scope of aggregate data for analyzing these risks to financial stability is very limited, because it is neither possible to differentiate between households that hold debt and those that do not, nor is it possible to combine the data on household debt with data on their assets in a reasonable way. Therefore, many authorities concerned with financial stability are increasingly using microdata to analyze such types of financial stability risks. Combining different microdata sources, we assess financial stability risks arising from indebted households in Austria. We define a financial margin for indebted households and stress test each indebted household against a range of financial shocks (changes in interest rates, unemployment rate, asset prices, exchange rates and repayment vehicle yields).

This study is a first attempt to get some insight into Austrian households' ability to pay and their financial distress. The available data are far from ideal, especially in terms of sample size and due to the absence of a joint dataset that includes real estate wealth, financial wealth and all kinds of household debt and expenses. The study should also be regarded as a test for future possibilities of research on financial stability by stress testing that may open up as soon as data from the new Eurosystem Household Finance and Consumption Survey, which will include all the necessary information in one dataset, will be available.

1 Introduction

Over the past decades, household debt increased both in absolute and relative terms in almost all OECD countries (see e.g. Girouard et al., 2006). Chart 1 illustrates this fact for Austria and the euro area by showing debt levels as a share of GDP and disposable household income. The difference in the developments observed in the euro area and in Austria from 2006 onward is mainly at-

Chart 1

Household Debt in Austria and the Euro Area
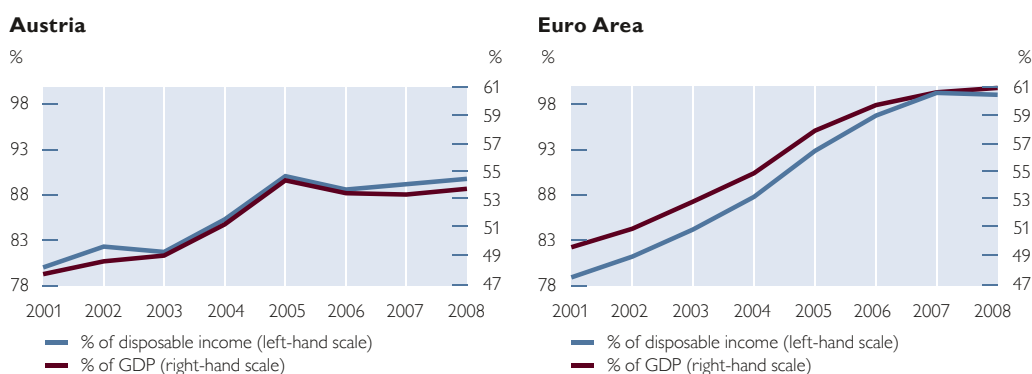
Source: ECB, OeNB.

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tributable to the strong expansion of household debt in Spain and France.

Total household debt as a percentage of households' total disposable income is a particularly common measure to assess financial stability risks. This measure is important because the debt-servicing ability of indebted households influences financial stability through different channels. Clearly, banks' losses on their loans to households is one important channel. Furthermore, households with a low or decreasing ability to service their debt may reduce spending; as a consequence, the demand for goods and services in the economy would decline, which, in turn, could have negative effects on companies and their ability to service their bank debt.

The scope of aggregate data for analyzing these risks to financial stability is very limited, as it is neither possible to differentiate between households that hold debt and those that do not, nor is it possible to combine the data on household debt with data on their assets in a reasonable way. As the U.S. subprime crisis recently showed, even a relatively small number of indebted households can produce considerable turmoil if the sustainability of their debt is in question. Therefore, many authorities concerned with financial stability are increasingly using microdata to analyze such types of financial stability risks. Similar to banks, central banks conduct stress tests of banks to assess these risks, which are a well-proven tool to assess risks in the banking sector. To this end, central banks collect data from banks to model stress scenarios in order to get an idea of possible future bank losses and their effects on the financial system as a whole. Banks, for their part, compile data on their (potential) clients at the household level to decide about the size of the loans they can grant to their customers (risk vs. profit assessment).

Under a reasonable risk management framework, these data should typically include household income, household structure and – possibly – household wealth.

To our knowledge, Austrian banks are currently using only internal data in their loan decisions, such as loan-to-value ratios, household income (if known) and maturities as well as historical probabilities of default and loss given default data by country and product. Furthermore they may use data on customers' creditworthiness provided by *Kreditschutzverband von 1870* (a company specializing in business data and debtor management). As far as we know, banks do not have access to any public registers (e.g. tax registers) or use information on households from surveys. On the basis of at least implicit assumptions about the future living expenses and behavior of these households, banks calculate the size of the loan they can grant to a customer. Usually this assessment exercise takes place before a loan (or new loan) to a household is approved.

The use of such data can entail numerous problems. First of all, the information is asymmetric. While the (potential) customers are interested in getting the highest loan levels at the best conditions, the banks aim to give their customers the worst conditions for the highest loan level the household in question could afford, given its financial situation for the duration of the loan. Second, there is uncertainty about future interest rate developments. This risk may be the banks' (in the case of fixed rate loans) or the customers' (in the case of variable rate loans). In either situation, the players need to take into account this risk to optimize their behavior. Therefore, every loan contract can be considered a game: On the one hand, in order to play these games well and ensure maximum profit (after the

decision about the level of risk has been made), banks need to gather the described information to be able to estimate the future financial situation of the household during the duration of the loan. On the other hand, customers have an incentive to overstate their financial situation and prospects. Ultimately, though, the customers' financial situation and prospects may not be overstated, because what counts is very often not only the personal finances of the borrower but those of the household as a whole; in some cases, even the wealth of people outside the household in question may be relevant, as may be forms of wealth about which banks typically do not collect data (e.g. jewelry, expected future inheritances etc.). The repayment duration may take up to 25 or 30 years, and, obviously, the financial situation of a household may change very fast because of unemployment, illnesses, divorces, inheritances and other unexpected events. It is not clear how often banks thoroughly reassess their customers' financial situation, which is a costly process. Of course, banks have some information: They can monitor withdrawals from and incoming payments on their customers' accounts. However, households may have accounts at other banks too, their financial situation may change without the bank noticing, or they may have loans at other banks or financial institutions. Even if banks have some idea about a household's probability of default, it is questionable how up to date these probabilities of default are. Likewise, in central banks' stress tests there are typically neither heterogeneous probabilities of default for households nor are there different risks of households, e.g. the probability of getting unemployed.

In addition to stress testing banks' portfolios – including household loans – some central banks recently started to stress test households directly to complement their analysis of risks of bank losses and to assess the risk of declining demand and the risks to the economy as a whole if the share of distressed households rises.

Johansson and Persson (2006) conducted a micro analysis of Swedish households' ability to pay. After identifying financially distressed households by calculating a financial margin, i.e. household income minus debt service and other necessary running costs (such as food and clothes), the authors introduce shocks, such as an unemployment shock and an interest rate shock, to examine how the percentage of distressed households would change. Under the assumption that these households have a probability of default of 1, they calculate possible bank losses by deducting a household's wealth from its debt. Vatne (2006) finds that financial margins for Norwegian households increased substantially over the period from 1987 to 2004, implying a decreasing risk to financial stability. Zajaczkowski and Zochowski (2007) claim that despite strong credit growth, the payback ability of households did not deteriorate in Poland. Herrala and Kauko (2007) identify a share of 13% to 19% of distressed households in Finland for different sample years. In its report "Financial stability 2007," Danmarks Nationalbank stress tests Danish households in a way similar to that used by Johansson and Persson (2006). Danmarks Nationalbank's analysis shows that even in extreme scenarios of high unemployment and high interest rates, the debt level of the household sector would not threaten financial stability through high bank losses. These results, however, are highly sensitive to the definition of households' necessary running costs. For Chile, Fuenzalida and Ruiz-Tagle (2009) define financially distressed households

as those with excess expenses over income of 20% and a ratio of debt service to income of above 50%. According to their calculations, 14% of indebted households (holding 20% of total debt) are financially distressed. The authors also find that financial stability is not significantly affected by high unemployment levels. May and Tudela (2005) follow a different approach. Instead of calculating financial margins, they estimate predicted probabilities of mortgage payment problems in England and find that a ratio of debt service to income of 20% or above is associated with a significantly higher probability of mortgage payment problems. Holló and Papp (2007) use several approaches including financial margins and predicted probabilities to find that depending on the methods used, the average share of vulnerable households in Hungary ranged between 2% and 7.4%. According to their results, the situation is unfavorable in that debt is concentrated in the group of risky households, even though most of it is collateralized. For the case of Austria, Beer and Schürz (2007) did not have the necessary information to calculate financial margins. Instead, they define financially distressed households as those that have a debt service-to-income ratio of above 30%. They find that between 9% and 9.5% of Austrian households are distressed and that increases in repayment obligations make more households vulnerable than increases in unemployment.

In this paper, we combine different microdata sources and assess financial stability risks arising from indebted households in Austria. We define a financial margin for indebted households and stress test each indebted household included in the OeNB's Household Survey on Housing Wealth against different financial and economic shocks, i.e. changes in interest rates, asset prices, exchange rates and repayment vehicle yields as well as a rise in unemployment.

2 Data, Definitions and Methodology

The main dataset we use in this paper is the OeNB's Household Survey on Housing Wealth 2008 (HSHW 2008). The HSHW 2008 was conducted as a pilot project for the future comprehensive Eurosystem Household Finance and Consumption Survey. The HSHW 2008 is a representative household survey investigating the housing wealth of Austrian households. The respondents were either the owners or tenants of the respective household's primary residence at the time of the interview. The survey focused on the ownership of the respective house or apartment and of additional real estate belonging to any of the household members as well as on the household's related liabilities. Furthermore, the study compiled detailed socioeconomic characteristics and data concerning intergenerational transfers in connection with housing wealth (see Wagner and Zottel, 2009, and Fessler et al., 2009).

In order to deal with item nonresponse, missing observations were multiply imputed using chained equations (see Albacete et al., 2010). To date, no dataset is available for Austria including all necessary information to calculate proper financial margins for individual households and loan losses for banks. This is why we use out-of-sample prediction to estimate the missing information from other data sources (see Johansson and Persson, 2006, and Zajaczkowski and Zochowski, 2007). The missing variables to be predicted are minimum expenses (for the calculation of financial margins) and financial wealth (for the calculation of bank losses). To predict the minimum expenses for the indebted households in the HSHW 2008, we use

two different data sources and an ad hoc variant to show the different impacts of each method. We use (1) the EU Statistics on Income and Living Conditions (EU-SILC) 2008 (for detailed information, see Statistics Austria, 2008), (2) the Austrian Consumption Survey 2004/05 and (3) an ad hoc method based on the minimum social benefits granted.

Each of these three variants gives us the information necessary for calculating financial margins for the indebted households, which in turn enables us to conduct stress tests. To assess possible bank losses, we also predict data on households' financial wealth. Whereas the HSHW 2008 includes real estate wealth, it does not include any information on financial wealth. Therefore we use data from the OeNB's Survey on Financial Household Wealth 2004 (SFHW 2004) to estimate financial wealth for the indebted households in

the HSHW 2008. Chart 2 shows a schematic representation of the different steps of our analysis.

In this study, we concentrate on the debt homeowners have taken out to build or purchase their primary residence. For these loans we have detailed information on value, interests, maturity, back payments, type and currency. We disregard housing loans taken out by tenants, loans of homeowners for other housing than their home and consumption loans because information on the latter is insufficient in the HSHW. Nevertheless, from the SFHW we know that around 85% of total household debt in Austria is housing debt. Given the fact[2] that around 83% of housing debt is debt taken out for the purchase of a primary residence, our study should cover around 71% of the total debt of households. Furthermore, indebted households' average consump-

<div align="right">Chart 2</div>

Schematic Representation of the Analysis
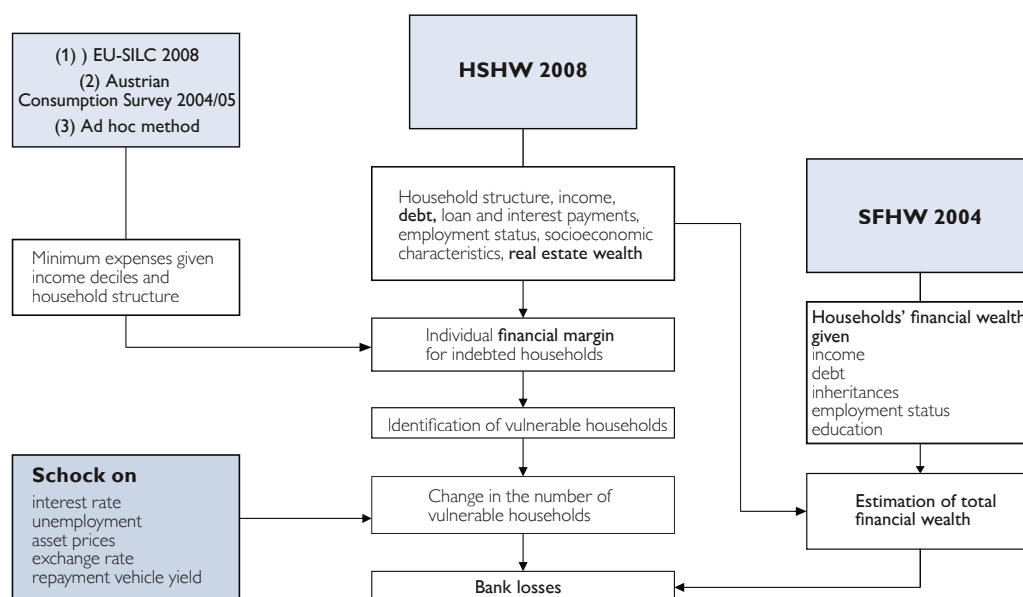
Source: OeNB.

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[2] According to the OeNB's 2007 survey on housing financing.

tion debt is in general much smaller than their average housing debt; likewise, tenants' average housing debt is much smaller than homeowners' average housing debt. The same is true for back payments. That is why we believe that excluding these loans should not have a significant impact on potential bank losses. Even in financial accounts data, which refer to the household sector (including also self-employed people, nonprofit institutions serving households and private foundations) – and do not classify all loans taken out for housing purposes as housing loans – housing loans accounted for some 61.5% of households' credit liabilities, while consumer loans accounted for 17.5% and "other lending" (e.g. loans to self-employed persons) for 21% in 2007.

Of the 2,081 households included in the HSHW survey, around 22% have housing-related liabilities. We exclude tenants' housing loans and homeowners' loans for other housing than their home, which leaves us 17% (360 observations) of the total sample of households which we consider to be relevant in our analysis.

Table 1 compares the subsample of indebted homeowners used in our analysis with the rest of the dataset. While this subsample consists of young, highly educated households with above-average household size, income and probability of employment, it is also the subsample with the highest concentration of debt.

Chart 3 shows that among indebted homeowners, too, a disproportionately large part of housing wealth and debt is held by higher-income households (Albacete and Wagner, 2009). The positive correlation between debt and wealth also exists for financial wealth (Fessler and Mooslechner, 2008).

Clearly, 360 households is a relatively small sample size. Furthermore, we apply prediction methods in order to calculate financial margins and the amount of bank losses. While these drawbacks of the analysis are problematic, we still hope to get some insight into the financial stress of households

Table 1

## Descriptives of Indebted and Non-Indebted Homeowners and Tenants

	Homeowners		Tenants
	indebted	non-indebted[1]	
Tenant/Homeowner			
Age	44	55	45
University degree	17.5%	9.2%	9.3%
Unemployed	0.9%	1.1%	4.6%
Employed	79.1%	53.5%	64.3%
Household			
Number of children (<18 years of age)	0.84	0.34	0.44
Number of adults	2.08	2.08	1.60
Mean monthly net income (EUR)	3.029	2.623	2.140
Mean imputed financial wealth (EUR)	54.047	49.105	22.006
Mean housing wealth (EUR)	314.654	389.314	131.954
Mean total housing debt (EUR)	92.850	1.855	2.604
Foreign currency housing loans for primary residence	29.8%	0.0%	0.0%
Mean number of loans among borrowers	1.3	1.2	1.1
N	360	725	996

Source: Authors' calculations.

[1] "Non-indebted" refers to households that did not take out a loan to build or purchase their primary residence; these households may have taken out other housing loans for other residences, though.

Chart 3

**Distribution of Austrian Households'
Debt and Wealth[1] per Income Quartile**

%
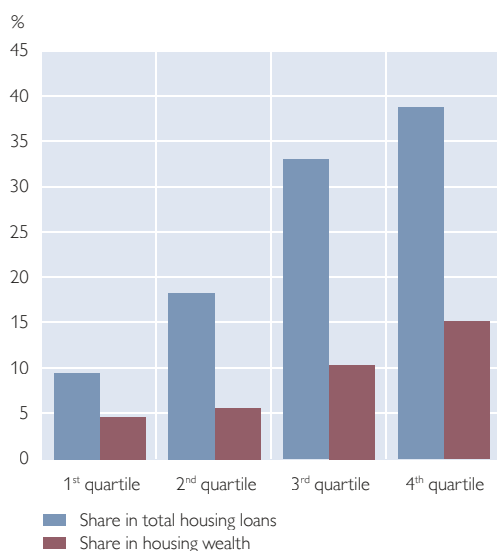
Source: OeNB, ECB.

[1] Calculated only for households with housing loans.

under different scenarios. Also, we view the analysis as a test for possible research using data from the Eurosystem Household Finance and Consumption Survey, which will be available in 2011.

2.1 Financial Margins

To show the different impacts of using different data sources to calculate a financial margin, we use three different variants with two different data sources and one ad hoc variant. All of these are used in the existing literature.

We define the financial margin FM_i of a household i as

$$FM_i := Y_i - BC_i - DS_i, \quad \text{(Def. 1)}$$

where Y_i is disposable household income, BC_i is basic consumption and DS_i is debt service. BC_i should cover minimum basic consumption for a given income decile and household structure.

Financial margins are therefore a measure of how well a household is able to make ends meet. While Y_i and DS_i are available for each household analyzed in the HSHW, we need to predict BC_i. We use (1) the EU Statistics on Income and Living Conditions (EU-SILC) 2008 (for detailed information, see Statistics Austria, 2008), (2) the Austrian Consumption Survey 2004/05 and (3) an ad hoc method based on the minimum of social benefits granted to predict BC_i for the indebted households in the HSHW 2008.

(1) EU-SILC 2008

We use a question from the EU-SILC survey about the minimum amount of net income the household would need to just be able to make ends meet. This variable should in principle cover all necessary expenses. It can be split up into two parts: On the one hand, it should include basic consumption, such as expenses on food, clothes, transportation, childcare, heating, etc. On the other hand, it should include rent (for tenants) or debt service (for indebted homeowners). Therefore, to get basic consumption BC_i from this measure of basic living expenses, we subtract rent and debt service in the EU-SILC dataset.[3] To map BC_i to the HSHW dataset, we estimate equation (1) on each household income decile in the EU-SILC and use the resulting coefficients to predict the corresponding values of BC_i for each household in the HSHW dataset,

$$ln(BC_i) = \beta_1 Y_i + \beta_2 A_i + \beta_3 C_i + \gamma' S_i + \varepsilon_i, \quad \text{(1)}$$

where Y_i is household net income, A_i is the number of adults and C_i the number of children living in the household. S_i is

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[3] Note that we subtract debt service in the EU-SILC survey as we prefer to calculate the financial margin using the debt service variable from the HSHW survey, which has much richer information on the liability side.

a vector with dummies for eight of the nine Austrian provinces and ε_i is a normally distributed error term with zero mean and σ^2 variance. The fact that income and the number of adults and children are determinants of a household's day-to-day basic consumption needs is unambiguously clear. We add dummies for Austria's provinces to control for possible differences in price levels.

(2) Austrian Consumption Survey 2004/05

As a second variant, we use the expenses on food, clothes, electricity, heating and other maintenance expenses from the Austrian Consumption Survey 2004/05. We regress this measure of basic consumption, which is available for every household according to equation (1). This time, we do not apply decile regression but estimate on the whole dataset and introduce a constant.[4] Again, we then use the resulting coefficients to predict BC_i for each household in the HSHW dataset.

(3) ad hoc method based on minimum social benefits

As a third variant, we use an ad hoc method based on minimum social benefits. Social benefit systems vary across Austria's provinces. We choose the minimum social benefits of the province of Vienna (excluding benefits for rents) granted to single-person households ($\overline{BC}_{sph}$) as a measure of minimum basic consumption. Basic consumption of a household is then defined for each household in the HSHW as

$$BC_i := \overline{BC}_{sph} \times ES_i, \quad \text{(Def. 2)}$$

where ES_i is the inverted new OECD equivalence scale.[5]

2.2 Probabilities of Default, Exposure at Default and Loss Given Default

The percentage of vulnerable households is the key measure to monitor the resilience of households under different shocks, such as employment shocks and changes in interest rates, asset prices, exchange rates and repayment vehicle yields. It is, of course, not the key measure to monitor possible bank losses. In order to measure possible bank losses under different stress scenarios, we need to take into account the share of total debt held by vulnerable households as well as these households' assets. We assume a probability of default for each household, pd_i. A probability of default of 1 is assigned to a vulnerable household, $(FM_i < 0)$, whereas a probability of default of 0 is assigned to other households, $(FM_i \geq 0)$. Now we can define the exposure at default (EAD), which measures the percentage share of total debt held by vulnerable households,

$$EAD := \frac{\sum_i pd_i D_i}{\sum_i D_i} \times 100, \quad \text{(Def. 3)}$$

where D_i is the debt of household i. The HSHW includes data on households' real estate wealth but no data on their financial wealth. Therefore, we define two measures of loss given default (LGD) in percent, where the first measures the share of debt held by vulnerable

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[4] We do not apply a decile regression because the income variable in the Austrian consumption survey is not as precise as that in the EU-SILC. The results are pretty robust to the methods used, though.

[5] The weights are normally used to produce equivalence household income by multiplying household income by 1/ES, where ES is 1 for single person households; the weight increases by 0.5 each for additional adults (>14 years of age) and by 0.3 each for children (<14 years of age).

households that is not covered by their real estate wealth,

$$LGD_1 := \frac{\sum_i pd_i N_i^1}{\sum_i D_i} \times 100, \text{ with}$$

(Def. 4)

$$N_i^1 = \begin{cases} D_i - REW_i \text{ if } REW_i < D_i \\ 0 \text{ otherwise} \end{cases}$$

where REW_i is the real estate wealth of household i.

Since most households do not only hold real estate wealth but also financial wealth, LGD_1 can be seen as an upper limit for bank losses. For the second measure of LGD, we need to impute financial wealth from the SFHW. The HSHW includes a huge number of socioeconomic variables and indicators about whether a household holds at least some financial wealth of a certain type (e.g. stocks, savings accounts, etc.). These variables and indicators are also included in the SFHW, so we can use them for a prediction based on regression. We estimate equation (2) on SFHW data and use the resulting coefficients to estimate total financial assets (TFA) values for each household in the HSHW dataset,

$$ln(TFA_i) = \alpha + \beta_1 Y_i + \beta_2 E_i + \\ + \beta_3 O_i + \gamma' X_i + \varepsilon_i,$$

(2)

where α is a constant, Y_i represents household income, E_i is the level of education of the household head[6], O_i stands for the household head's occupational status, X_i is a vector of further control variables, such as the household head's age and age squared, a dummy for homeownership, a dummy for living in a big city (Vienna) or not, and a dummy for holding risky assets (stocks, bonds, mutual fund shares), and ε_i is a normally distributed error term with zero mean and σ^2 variance. We adjust the resulting values using the increase in overall financial wealth from financial accounts data. While the fit of the model on SFHW data is arguably good, the necessity to predict TFA is clearly one of the many drawbacks we face because of the lack of a dataset including TFA, REW, debt, income and consumption (all these measures will be included in the upcoming Eurosystem Household Finance and Consumption Survey). After predicting via equation (2), we define our second measure of LGD in percent,

$$LGD_2 := \frac{\sum_i pd_i N_i^2}{\sum_i D_i} \times 100, \text{ with}$$

(Def. 5)

$$N_i^2 = \begin{cases} D_i - REW_i - TFA_i \text{ if } REW_i + TFA_i < D_i \\ 0 \text{ otherwise} \end{cases}$$

3 Descriptives

Table 2 shows the percentage of vulnerable households, EAD, LGD_1 and LGD_2 for all three variants for which we calculated financial margins.

The percentage of households identified as vulnerable varies between 9.2% (variant 1) and 15.6% (variant 3), which seem to be plausible numbers. One possible benchmark against which we can compare our numbers in terms of plausibility is the EU-SILC dataset itself, which contains all the necessary information for calculating financial margins.[7] We find a share of around 10%

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[6] In the HSHW, the household head is defined as the tenant or owner of the primary residence.

[7] Note that EADs and LGDs cannot be calculated with EU-SILC 2008 data. For calculating the financial margin, we subtract from household income the minimum amount of net income a household needs to just be able to make ends meet (which includes debt service).

Table 2

Percentage of Vulnerable Households, Exposure at Default and Loss Given Default

Income quartile	Variant (1)				Variant (2)				Variant (3)			
	% of vulnerable house-holds	EAD	LGD$_1$	LGD$_2$	% of vulnerable house-holds	EAD	LGD$_1$	LGD$_2$	% of vulnerable house-holds	EAD	LGD$_1$	LGD$_2$
1	56.7	5.9	1.0	0.9	59.6	6.4	1.2	1.1	70.5	7.1	1.2	1.1
2	14.3	7.1	1.3	1.1	18.3	9.2	2.3	2.0	27.6	11.8	2.4	2.0
3	1.2	0.5	0.0	0.0	5.3	4.4	1.0	0.6	7.9	5.7	1.3	0.7
4	1.0	0.8	0.2	0.1	0.9	1.9	0.5	0.3	1.1	2.0	0.5	0.3
Total	9.2	14.3	2.6	2.1	11.7	21.9	5.0	4.0	15.6	26.5	5.4	4.1

Source: Authors' calculations.

Note: Variant (1) uses EU-SILC data as the source for imputing basic household consumption, variant (2) uses the Austrian Consumption Survey 2004/05, and variant (3) uses an ad hoc method based on minimum social benefits.

of vulnerable households. Our numbers are also in line with the results of Beer and Schürz (2007), who find a 9% to 9.5% share of vulnerable Austrian households.

By predicting mean expenditure values from an expenditure survey across all income deciles, Johansson and Persson (2006) find that 6.3% of indebted Swedish households (accounting for 5.6% of total debt) are vulnerable. In his study on Norway, Vatne (2006) identifies 19% vulnerable households (holding 16% of total debt) by defining the level of necessary consumption for an average household over varying household sizes. Danmarks National-bank (2007) finds that the Danish EAD ranges between 4% and 15.5%, depending on the definition of basic consumption in the financial margin. In a study on Chile, Fuenzalida and Ruiz-Tagle (2009) use slightly different definitions of a negative financial margin and find that 9.5% to 13.6% of Chilean indebted households (holding 16.1% to 20.2% of total debt) are vulnerable. Zajaczkowski and Zochowski (2007) find that around 12% of Polish households were vulnerable in 2006 and held around 15% of total household debt. The authors use a minimum social ben-

efit concept to define basic consumption. According to Herrala and Kauko (2007), who use quite a different approach based on households' opinions, 13% to 19% of indebted Finnish households are distressed. Using several approaches such as financial margins and opinions, Holló and Papp (2007) find that the share of vulnerable households in Hungary ranges between 2% and 7.4%, while EAD is between 3.5% and 22%.

In Austria, vulnerable homeowning households have, on average, lower incomes, higher debt and a higher likelihood of a female household head than non-vulnerable households. Furthermore, it is remarkable that they have, on average, more loans (1.5 loans instead of 1.3), which could be indicative of different — maybe informal — lending channels.

Table 2 suggests that the share of vulnerable households is quite sensitive to the applied method of identification. At the same time, the patterns of these shares in relative terms over the income quartiles and concerning EAD and LGD seem to be quite robust across the different methods applied. The percentage of vulnerable households, i.e. households with a negative financial margin, decreases with household in-

come. EADs are highest in the second income quartile, even though the share of vulnerable households is much lower than in the first income quartile. In two of the three scenarios, the vulnerable households in the highest income quartile hold a disproportionately high amount of debt. The same is also true for the total in all variants. This shows that the few vulnerable households in the higher income quartiles hold, on average, much higher amounts of debt than lower-income households. LGD_1 and LGD_2 results show that most liabilities are covered by households' assets which, in the case of indebted homeowners, are mostly real estate assets.

The values of our vulnerability indicators (share of vulnerable households, EAD or LGD) should not be compared directly with those obtained in bank stress tests. We may use the same term, but there are several differences. First, our indicators additionally capture household lending channels other than banks, such as loans from other households, employers or other private lenders. These loans are probably subject to higher risks of debt default because of the lack of monitoring in these more informal channels. Second, our definition of vulnerable households assumes that as soon as a household has a negative financial margin, its probability of default is 1. This is of course a very strong assumption, because in reality, such a household is likely to find other ways of making ends meet, such as renegotiating the loan contract with the bank or asking family or friends for help. In particular, the incentive of searching for such alternative solutions could be higher in Austria than in other countries, because the cost of personal bankruptcy is much higher: In Austria, the insolvent person's entire wealth and income will be liquidated up to a certain minimum level; by comparison, in some U.S. states, only debt securities are liquidated.

4 Stress Scenarios

In this section, we show how the share of vulnerable households shifts under different stress scenarios and calculate the resulting EADs and LGDs of those shifts. While the previous section provided some insight into the amount of vulnerable households and what this means in terms of lending risks and the risks of losses for banks, this section aims to give us some idea about the resilience of households against different shocks. Comparing the effects of different shocks could be valuable in terms of policy advice, even if the share of vulnerable households can in general be over- or understated and we cover only first-round effects.

We performed the stress tests using all three definitions of basic consumption, but for reasons of clarity, we present the results of variant (1) only, where basic consumption is imputed from EU-SILC 2008 data. We take the first variant to calculate bank losses because it delivers the most plausible share of vulnerable households compared with the EU-SILC benchmark. These results are also representative – in terms of directions and relative magnitude of the changes – of the other two definitions.

4.1 Rising Interest Rates

A rise in the interest rate is a shock to the households' debt service DS_i, but – at least in the short term – just for households which have variable interest loans. We assume that in the long run, even fixed interest loans are affected by such a shock due to a renegotiation of interest rates. 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. In our sample, around 66% of indebted households hold at least one variable interest loan. For these loans we increase the debt service in line with the assumed rise in the interest rate and assuming that the loan (and interest) is still repaid according to schedule, i.e. without expanding the maturity of the loan. In the long-term scenario, we make these adjustments also for the remaining (fixed rate) loans.

Table 3 describes the resulting changes in the share of vulnerable households, EAD, LGD_1 and LGD_2 different increases in the interest rate.

Increases in interest rates have a strong positive effect on the proportion of vulnerable households. A rise by 1 percentage point raises the share of vulnerable households in the short (long) run by 0.6 percentage points (0.9 percentage points). In an extreme scenario, where interest rates increase by 3 percentage points, the share of vulnerable households rises by even 2.8 percentage points (3.8 percentage points), which is a 30% (41%) higher share than in the baseline scenario. These effects are the strongest among the results of all stress scenarios, as every household's debt service – regardless of the type of loan – is affected by such shock.[8] The effect on debt at risk or EAD is even stronger than that on the proportion of vulnerable households. In the extreme scenario of an interest rate increase by 3 percentage points, EAD rises by 50% in the short and 64% in the long run. This means that the debt of the newly identified vulnerable households is higher than the debt of those which are vulnerable in the baseline scenario. The former are households with higher incomes, as debt rises with household income in the group of indebted households. If we take into account wealth, the LGD indicators show that most of the debt of newly identified vulnerable households is covered by their wealth, mainly real estate. The fact that LGD_2 does not rise after the second and third increase in interest rates supports the idea that the newly identified vulnerable households are wealthier. Finally, it is worth mentioning that the short-term effects are quite substantial in comparison with the long-term effects, which can

Table 3

Short- and Long-Term Effects of Interest Rate Increases

		Interest rate increase by		
	Baseline scenario	1 percentage point	2 percentage points	3 percentage points
Short-term				
% of vulnerable households	9.2	9.8	11.1	12.0
EAD	14.3	16.8	19.8	21.4
LGD_1	2.6	3.7	3.9	4.1
LGD_2	2.1	2.9	2.9	2.9
Long-term				
% of vulnerable households	9.2	10.1	11.9	13.0
EAD	14.3	17.6	21.3	23.5
LGD_1	2.6	4.0	4.3	4.4
LGD_2	2.1	3.2	3.3	3.3

Source: Authors' calculations.

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[8] *With the rare exception of zero interest loans (mainly loans from friends and family).*

be explained by the high share of variable rate loans in Austria.

4.2 Rising Unemployment

When an employed household member loses his or her job, this is a shock to the household's income Y_i. As not every working person in an economy has the same probability of becoming unemployed, we first need to define the probability of becoming unemployed for each working homeowner in our sample. Note that we do not model unemployment for other working persons in the same household because we do not have enough information for a proper model. This, of course, implies that the decline in income for households with more household members may be underestimated because their contribution to household income is not affected by our unemployment stress scenario. We estimate a logistic model – which is here represented as single layer perceptron – to get probabilities of unemployment for all homeowners pu_i,

$$pu_i = \Pr(unemployed \mid X) =$$
$$= \Lambda(\beta' X) = \frac{1}{1 + e^{-\beta' X}}, \qquad (3)$$

where $\Lambda(\cdot)$ is the cumulative distribution function of the logistic distribution, and X is a vector of independent variables including gender, education, household income, a dummy for a partner times a dummy for employment of the partner, province, number of adults, number of children, age and age squared of the household head. Logit coefficients show expected signs, e.g. higher education significantly lowers the probability of unemployment, and having an employed partner significantly increases the probability of unemployment, which can be ascribed to the broader base of income resources in the household.

To calculate a rise in the unemployment rate, we use the resulting coefficients to estimate the probability of unemployment by increasing the constant of the model until the rate of unemployment matches a certain value. After a probability of being unemployed is assigned to each person, we draw from a uniform distribution a random real number $\eta_i \in [0;1]$ for each single person. If $pu_i \geq \eta_i$, we designate the person as unemployed, assume that he or she receives 55% of the monthly salary in unemployment benefits according to the current Austrian unemployment benefit rules, and subtract 45% of the person's wage from total household income. We repeat these steps 1,000 times using Monte Carlo simulation, each time calculate the vulnerability indicators, and finally take the mean of each one of these indicators over all simulated draws.

Table 4 describes the changes in the share of vulnerable households, EAD,

Table 4

Effects of a Rise in the Unemployment Rate

	Baseline scenario	Increase in overall unemployment rate by		
		1 percentage point	2 percentage points	3 percentage points
% of vulnerable households (mean)	9.2	9.3	9.3	9.4
Mean EAD	14.3	14.4	14.5	14.6
Mean LGD_1	2.6	2.6	2.6	2.6
Mean LGD_2	2.1	2.1	2.1	2.1

Source: Authors' calculations.

LGD_1 and LGD_2 resulting from different changes in the overall unemployment rate.[9]

A 1 percentage point increase in the overall unemployment rate raises the share of vulnerable households from 9.2% to 9.3% and the share of their debt from 14.3% to 14.4%, but it does not change the risk of bank losses. Even the extreme scenario of an increase in the overall unemployment rate by 3 percentage points does not essentially change the LGD indicators. These results are in line with those of other studies. For example, Johansson and Persson (2006) find that an increase in the unemployment rate by 1 percentage point makes the proportion of vulnerable households and the EAD rise by 0.2 percentage points, while LGD remains unchanged, even in the extreme scenario.

Thus, the effects of unemployment shocks are much weaker than those of interest rate shocks. There are two reasons for this. First, an unemployment shock can be at least partially absorbed by a household using the income of other household members who are still in employment. Therefore, single or single-parent households are much more vulnerable to unemployment shocks than other households. Second, although every employed person is exposed to the risk of becoming unemployed, the group of homeowners, on which we focus, certainly has a lower probability of becoming unemployed than other groups (e.g. tenants). Table 1 shows that only 0.9% of indebted homeowners are unemployed, while this rate is 4.6% for tenants. Likewise, the share of homeowners with a university degree is considerably higher (17.5%) than the share of tenants with such a degree (9.3%), which also increases the proba-

bility that the former do not lose their job. Finally, table 4 shows that, contrary to the interest rate shock scenario, the unemployment shock scenario tends to make low-income households vulnerable, as evidenced by the fact that the relative increase in the proportion of vulnerable households in the extreme scenario of a 3 percentage point increase in overall unemployment is higher (1.6%) than the increase in EAD (0.8%), suggesting that the new debt at risk is held by poorer households with relatively low levels of debt and wealth. This result makes perfect sense because our logistic model design allows the unemployment shock to be selective on those people who have a higher probability of becoming unemployed (e.g. less educated or low-income household heads).

4.3 Changes in Asset Prices

Changes in asset prices are shocks to households' real estate wealth or their total financial assets. Such changes should in principle affect LGD_1 and LGD_2 only, but for households with bullet loans, they also affect the amount saved in the repayment vehicle (see section 4.4.2). Therefore, asset price shocks can also change the share of vulnerable households and thus *EAD*,

Table 5

Effects of Asset Price Changes

	Decrease in real estate wealth by			
	0%	10%	20%	30%
Decrease in total financial wealth by				
0%	2.1	2.3	2.6	2.9
10%	2.1	2.4	2.7	3.0
20%	2.1	2.4	2.7	3.1
30%	2.2	2.5	2.8	3.1

Source: Authors' calculations.

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[9] *Based on the HSHW 2008 data, a change in the general unemployment rate by 1 percentage point translates into a 0.4 percentage point change in the unemployment rate of homeowners.*

which is not considered in this scenario. Table 5 describes the changes in LGD_2 resulting from different changes in asset prices.

According to table 5, LGD_2 is much more sensitive to changes in real estate wealth than to changes in financial wealth. This is not very surprising, given that the real estate wealth of the households covered here is six times higher than their financial wealth (see table 1). In a scenario in which house prices and financial asset prices fall by 30%, LGD increases by 50% from 2.1% to 3.1%. These are the second strongest effects – after the long-term effects of an interest rate shock – that our stress tests showed. However, a drop in house prices by as much as 30% is a very low probability event, at least for Austria.

4.4 Other Shocks

4.4.1 Changes in Exchange Rates

A rise in the exchange rate is a shock to the households' debt service DS_t, but just for the households with foreign currency loans.[10] In Austria, foreign currency loans – especially loans denominated in Swiss francs – are quite common (Beer et al., 2010). Around 29% of indebted households have at least one foreign currency loan. Mostly, these loans are bullet loans, which means that the entire principal of the loan is due at the end of the loan term and the borrower saves for repayment in a repayment vehicle. For our stress test, we construct a hypothetical debt service by defining the necessary regular payments a household has to make into repayment vehicles given the

amount and maturity of the loan and by defining an assumed typical yield for each repayment vehicle. A change in the exchange rate affects the regular payments for the rest of the maturity. For example, if the value of the Swiss franc against the euro increases, the total value of the loan rises, too, and the regular payments into the repayment vehicle rise accordingly. Note that in this scenario, we neglect possible changes in the interest for (or value of) the money already paid into the repayment vehicle before the shock occurs, and we also neglect possible changes that might occur at a later time. Furthermore, we again assume that the maturity does not change and that the households need to adapt their regular payments immediately. Table 6 describes the resulting changes in the share of vulnerable households, EAD, LGD_1 and LGD_2 for different changes in the exchange rate.

The appreciation of the foreign currency in which households hold their debt has only moderate effects on the proportion of vulnerable house-

Table 6

Effects of an Appreciation of the Loan Currency against the Euro

	Baseline scenario	Appreciation by		
		1%	2%	5%
% of vulnerable households	9.2	9.4	9.4	9.8
EAD	14.3	14.6	14.6	15.1
LGD_1	2.6	2.7	2.7	2.7
LGD_2	2.1	2.2	2.2	2.2

Source: Authors' calculations.

[10] *We are aware of the fact that a change in exchange rates could also be a shock to households' income if the wages of household members are denominated in foreign currencies (e.g. if people work abroad or for foreign companies which pay their wages in foreign currency). Furthermore, an exchange rate shock would be less severe for a household which holds debt in foreign currency but at the same time earns income in the same currency. We ignore both possibilities in our stress test. As far as we know, foreign currency income is very uncommon in Austria.*

holds and EADs. For example, a 5% appreciation of the Swiss franc against the euro increases the share of vulnerable households from 9.2% to 9.8%, while the EAD rises from 14.3% to 15.1%. Still, even an appreciation by 1%, which translates into a rise in the share of vulnerable households by 0.2 percentage points, results in a small rise in LGDs.

Remarkably, an increase in the unemployment rate by 3 percentage points also translates into a 0.2 percentage point rise in the share of vulnerable households but has hardly any effect on LGD. Obviously, the households that are newly identified as vulnerable in the exchange rate scenario, especially those with a very small positive financial margin, hold comparably high amounts of debt. This is not surprising, as we know that foreign currency loans started to become popular in the late 1990s, and the outstanding debt in this category (mostly in terms of total debt minus cumulated payments into repayment vehicles) is still quite high, even that of higher-income households.

Furthermore, it is quite obvious that a 1% appreciation of the foreign currency is a more probable event than a 3 percentage point increase in unemployment. In the current economic situation, even appreciations by much more than 5% cannot be ruled out and would lead to much higher EADs and

LGDs. An appreciation by 30% would result in an LGD_1 of 3.4% and an LGD_2 of 2.6%, again even though just 29% are exposed to the shock.

4.4.2 Changes in the Repayment Vehicle Yield

In this scenario, we test the effect of a decrease in the assumed yields of the repayment vehicles. This is a shock to the households' (hypothetical) debt service DS_t, but just for those households which have bullet loans. Note that as in the last scenario, we neglect possible changes in the interest for (or value of) the money already paid into the repayment vehicle before the shock occurs, and we also neglect possible changes at a later point in time. Furthermore, we again assume that the maturity of the loans does not change and that the households need to adapt their regular payments immediately. Table 7 describes the resulting changes in the share of vulnerable households, EAD, LGD_1 and LGD_2 for different changes in the repayment vehicle yield.

The effects are very similar to those of the previous scenario, in which the foreign currency appreciates. A decrease in the repayment vehicle yield by 3 percentage points leads to a moderate rise in the proportion of vulnerable households from 9.2% to 9.6% and of the EAD from 14.3% to 15.4%. LGD_2 changes from 2.1% to

Table 7

Effects of a Decrease in the Assumed Yield of Repayment Vehicles for Bullet Loans

	Baseline scenario	Decrease in yield by		
		1 percentage point	2 percentage points	3 percentage points
% of vulnerable households	9.2	9.2	9.5	9.6
EAD	14.3	14.3	15.2	15.4
LGD_1	2.6	2.6	2.7	2.8
LGD_2	2.1	2.1	2.2	2.2

Source: Authors' calculations.

2.2%. This similarity is not surprising as most (72%)[11] foreign currency loans are bullet loans and therefore, the same households are hit by both shocks. The difference resides in the channel through which the shock is transmitted. While exchange rate shocks change the entire amount of the loan that has to be paid back at maturity, yield shocks increase the amount the household has to save regularly in order to pay back the whole loan amount at maturity. Through these two different channels, the two shocks increase the household's regular and/or its hypothetical debt service. Nevertheless, a decrease in the yield by 3 percentage points can be considered as quite a low probability event, because the majority of repayment vehicles used are life insurance products.

4.4.3 Combined Scenarios

We combine the two scenarios of a decrease in asset prices and an appreciation of the foreign currency in which loans are denominated to document the risks arising from foreign currency loans, which are mostly bullet loans linked to a repayment vehicle. In the unemployment scenario, an increase in vulnerable households by 0.2 percentage points has no effect on LGD_2. By contrast, in the combined scenario, a rise in the share of vulnerable households by 0.2 percentage points resulting from an appreciation of the foreign currency by 1% that goes hand in hand with a 20% decrease in wealth translates into a rise of LGD_2 by 0.8 percentage points. These differences clearly result from the heterogeneous structure of household debt among different types of households. Note that whereas most households are just exposed to interest rate shocks, unemployment shocks and asset price shocks, households with foreign currency bullet loans are exposed to all our shock scenarios – including exchange rate shocks and repayment vehicle yield shocks. In particular, the asset price shock reduces not only households' wealth but also parts of their cumulated payments into repayment vehicles, which our scenario does not cover.

In an unstable economic environment, combined scenarios may be quite likely. Under these scenarios, the households that are exposed to many of the risks assumed in the scenarios are hit hardest, and the banking sector's risk of loan losses increases as the risks multiply. Still, to model multiple shocks in a meaningful way, we would need much better data that allow much more elaborated models using micro simulations.

5 Conclusions

The sharp increase in household debt over the past decades has raised questions about the sustainability of this debt and about possible risks for the banking sector. As the U.S. subprime crisis and its repercussions recently demonstrated, even a relatively small number of indebted households can produce heavy turmoil if the sustainability of their debt is in question.

In the case of Austria, the relatively high share of foreign currency loans – usually bullet loans linked to repayment vehicles – is a reason for additional concern. In this case, a household takes on exchange rate risk combined with

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[11] *We think that this number could be understated as some households taking part in the survey may not have realized that paying into a repayment vehicle (instead of directly paying back the loan) implies having a bullet loan. This fact may also lead to a downward bias for the repayment vehicle scenario.*

the risk of a change in the value and yield of the repayment vehicle, i.e. the household acts as a carry trader.

Macrodata are of limited use in the analysis of the risks to financial stability resulting from household debt, as it is neither possible to differentiate between households that hold debt and those that do not, nor is it possible to combine data on households' debt with data on their assets. Furthermore, macrodata do not include information about which households hold the risky forms of debt, e.g. foreign currency loans, and which households hold enough assets to cover their debt. In addition, it remains unclear how up to date and complete the information of banks is about the vulnerability of their clients, as we discuss in section 1.

Given all these facts, many authorities dealing with financial stability are increasingly using microdata to analyze and predict financial stability risks resulting from household debt. We employ available Austrian microdata to get first insights into these risks. These data are far from ideal, and more comprehensive surveys, which include detailed information on households' assets and liabilities, like the upcoming Eurosystem Household Finance and Consumption Survey, are urgently needed.

Stress tests of banks usually use big datasets gathered from banks; information on individual households is very limited, though. In the recently conducted stress tests of households (using survey data), it is the other way round: The datasets are, in general, relatively small but the information on individual households is usually quite rich. Therefore, the stress tests are not substitutes but complements.

Stress tests of banks are arguably better suited for estimating the aggregate amounts of EAD and LGD and, therefore, better suited for getting an idea of possible bank losses under different scenarios. Stress tests of households using survey data may be superior in showing the mechanisms of possible default at the micro level and may, therefore, help identify groups of debtors which are especially vulnerable. Furthermore, they can show what shocks are particularly dangerous for different groups of households. Another advantage may be that certain measures of probabilities of default are not inferred from the past but can be based on an assessment of the actual household budget. Clearly, further research and the development of more elaborate methods are necessary.

Still, we find that the households holding the biggest part of total household debt, i.e. indebted homeowners who took out loans for their primary residence, have higher levels of education, income and wealth than the others. This finding ties in with international evidence (e.g. Johansson and Persson, 2006).

We analyze the debt of homeowners for their primary residence; our study therefore covers around 71% of households' total debt. Using different approaches, we find that around 9.2% to 15.6% of those are vulnerable, i.e. they have a negative financial margin. Under the assumption that all households with a negative financial margin have a probability of default of 1, the EAD is 14.3% and LGD_1 is 2.6% (considering only real estate wealth to cover debt) and LGD_2 is 2.1% (considering real estate and financial wealth). We stress the indebted households' finances by assuming different types of shock scenarios. The rising interest rate scenario has the strongest impact (even in the short term), due to the fact that around two-thirds of debtors in Austria have variable rate loans. The rising unemployment scenario shows fairly moderate effects. On the one hand, the probability

of homeowners getting unemployed is much lower than that of tenants, and the indebted homeowners group is, on average, better educated and has a higher income. Furthermore, those who get unemployed in the group of indebted homeowners are more likely to have a lower level of education, income and outstanding debt. This is why the increase in EAD is relatively small in relation to the increase in the share of vulnerable households compared with the other stress scenarios. We also check how changes in asset prices change LGD_2 and find that changes in real estate wealth are much more harmful than changes in total financial wealth.

Our stress tests of households holding debt denominated in foreign currency or holding bullet loans focused on an appreciation of the respective foreign currency relative to the euro and on changes in the repayment vehicle yield. Given the fact that just a small subsample of households is affected, the effects of these changes on the share of vulnerable households and the other measures are remarkable. Obviously, in particular households holding bullet loans that are denominated in foreign currency and linked to a repayment vehicle could suffer from a combination of the asset price, the exchange rate and the repayment vehicle yield scenarios, which, in turn, could multiply effects. Clearly, these households bear the highest risks in relation to their debt, as they are exposed to all the shock scenarios described here, and multiple shocks are by no means implausible.

All in all, the potential loan losses for banks resulting from shocks to Austrian households do not compromise financial stability as a whole. The risk that households bear is particularly high for those with foreign currency loans and bullet loans; since these loans are often a combination of the two, the resulting risks are multiplied.

However, the fact that around 10% of indebted households may have problems and need to reduce expenses to be able to service their debt if a shock occurs is worrisome. Also, it should be noted that this analysis does not include consumption credit debtors, who – even if the amount of their debt is, on average and in total, much smaller and therefore does not pose a threat to financial stability at all – are not as well off as indebted homeowners and may suffer more under their debt servicing duties.

References

Albacete, N., P. Fessler and K. Wagner. 2010. Multiple Imputation in the Austrian Household Survey of Housing Wealth 2008. Vienna: OeNB. Mimeo.

Albacete, N. and K. Wagner. 2009. Housing Finance in Austria. In: Monetary Policy & the Economy Q3/09. OeNB. 62–92.

Beer, C. and M. Schürz. 2007. Characteristics of Household Debt in Austria – Does Household Debt Pose a Threat to Financial Stability? Monetary Policy & the Economy Q2/07. OeNB. August. 58–79.

Beer, C., S. Ongena and P. Marcel. 2010. Borrowing in Foreign Currency: Austrian Households as Carry Traders. Journal of Banking and Finance (forthcoming).

Danmarks Nationalbank. Macro Stress Testing of Danish Households. In: Financial Stability 2007. 87–96.

Fessler, P., P. Mooslechner, K. Wagner and M. Schürz. 2009. Housing Wealth of Austrian Households. Monetary Policy & the Economy Q2/09. OeNB. 104–126.

Fessler, P. and P. Mooslechner. 2008. Arme Schuldner – Reiche Schuldner? Haushalts-verschuldung und Geldvermögen privater Haushalte auf Basis von Mikrodaten. In: Intervention. European Journal of Economics and Economic Policies 5(1). 31–45.

Fuenzalida, C. M. and V. J. Ruiz-Tagle. 2009. Households' Financial Vulnerability. Journal Economía Chilena (The Chilean Economy) 12(2). Central Bank of Chile. August. 35–53.

Girouard, N., M. Kennedy and C. André. 2006. Has the Rise in Debt Made Households More Vulnerable? OECD Economics Department Working Paper 535. www.olis.oecd.org/olis/2006doc.nsf/linkto/ECO-WKP(2006).

Herrala, R. and K. Kauko. 2007. Household Loan Loss Risk in Finland – Estimations and Simulations with Micro Data. Research Discussion Papers 5/2007. Bank of Finland.

Holló, D. and M. Papp. 2007. Assessing Household Credit Risk: Evidence from a Household Survey. Magyar Nemzeti Bank (The Central Bank of Hungary). MNB Occasional Papers 70.

Johansson, M. W. and M. Persson. 2006. Swedish Households' Indebtedness and Ability to Pay – A Household Level Study. In: Penning- och Valutapolitik 3/06. Sveriges Riksbank. 24–41.

May, O. and M. Tudela. 2005. When is Mortgage Indebtedness a Financial Burden to British Households? A Dynamic Probit Approach. Bank of England Working Paper 277.

Statistics Austria. 2008. Standard-Dokumentation, Metainformationen (Definitionen, Erläuter-ungen, Methoden, Qualität) zu EU-SILC 2008.

Vatne, B. H. 2006. How Large are the Financial Margins of Norwegian Households? An Analysis of Micro Data for the Period 1987–2004. Economic Bulletin 4/06(77). Norges Bank. 173–180.

Wagner, K. and S. Zottel. 2009. OeNB-Immobilienvermögenserhebung 2008 der privaten Haushalte – Beschreibung, verwendete Methoden und Bewertungsansätze. Statistiken – Daten & Analysen Q4/09. OeNB. 45–65.

Zajaczkowski, S. and D. Zochowski. 2007. Housing Loans Foreign Currency Risk and Supervisory Response: The Polish Case. Mimeo. National Bank of Poland.