EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

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Stress testing household balance sheets in Luxembourg

No 2254 / March 2019

Household Finance and Consumption Network (HFCN)

This paper contains research conducted within the Household Finance and Consumption Network (HFCN). The HFCN consists of survey specialists, statisticians and economists from the ECB, the national central banks of the Eurosystem and a number of national statistical institutes.

The HFCN is chaired by Ioannis Ganoulis (ECB) and Oreste Tristani (ECB). Michael Haliassos (Goethe University Frankfurt), Tullio Jappelli (University of Naples Federico II) and Arthur Kennickell act as external consultants, and Juha Honkkila (ECB) and Jiri Slacalek (ECB) as Secretaries.

The HFCN collects household-level data on households' finances and consumption in the euro area through a harmonised survey. The HFCN aims at studying in depth the micro-level structural information on euro area households' assets and liabilities. The objectives of the network are:

1) understanding economic behaviour of individual households, developments in aggregate variables and the interactions between the two;
2) evaluating the impact of shocks, policies and institutional changes on household portfolios and other variables;
3) understanding the implications of heterogeneity for aggregate variables;
4) estimating choices of different households and their reaction to economic shocks;
5) building and calibrating realistic economic models incorporating heterogeneous agents;
6) gaining insights into issues such as monetary policy transmission and financial stability.

The refereeing process of this paper has been co-ordinated by a team composed of Pirmin Fessler (Oesterreichische Nationalbank), Michael Haliassos (Goethe University Frankfurt), Tullio Jappelli (University of Naples Federico II), Juha Honkkila (ECB), Jiri Slacalek (ECB), Federica Teppa (De Nederlandsche Bank) and Philip Vermeulen (ECB).

The paper is released in order to make the results of HFCN research generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the author's own and do not necessarily reflect those of the ESCB.

Abstract

This paper uses representative individual household data from Luxembourg to evaluate how severe economic conditions could affect bank exposure to the household sector. Information on household income, expenses and liquid assets are used to calculate household-specific probabilities of default (PD), aggregate bank exposure at default (EAD) and aggregate bank loss given default (LGD). The exercise is repeated with scenarios combining severe but plausible shocks to real estate prices, bonds and stocks, household income and interest rates. Compared to the no-shock baseline, the LGD rises by a multiple of eight, reaching 4.2% of total bank exposure to the household sector. The high-stress scenario also generates a relatively high percentage of defaults among socio-economically disadvantaged households. Our main conclusion is that bank losses appear to be quite sensitive to financial stress, despite three mitigating factors in Luxembourg: indebted households tend to hold liquid assets that can help smooth shocks, household leverage tends to decline rapidly once mortgages have been serviced several years, and loan-to-value ratios at origination appear not to be excessive.

JEL-codes: D10, D14, E44, G01, G21

Keywords: Financial stability; HFCS; Household finance

Non technical summary

This paper uses individual household data from Luxembourg to evaluate how severe economic conditions could affect bank exposure to the resident household sector. This micro-data approach complements analyses based on aggregate data, which do not account for heterogeneity in the distribution of debt, collateral and income across the population of households.

We conduct a household stress test on data from a representative survey using methods applied at the International Monetary Fund, European Central Bank and other national central banks. First, we calculate the probability of default for individual households, using a measure of financial margin that combines information on their household income, expenses and liquid assets. We then calculate aggregate bank exposure at default (EAD) by multiplying these household-level probabilities of default by their corresponding volume of outstanding loans and summing across the population of households. Finally, we obtain aggregate bank loss given default (LGD) on household loans by assuming that banks recover real estate assets from defaulting households and liquidate them with a haircut. To simulate adverse economic conditions, we repeat the exercise using scenarios that combine severe but plausible shocks to real estate prices, bonds and stocks, household income and interest rates.

In the no-shock baseline, the average probability of default across indebted households is only 3.1%. On this basis, bank EAD would represent 4.7% of all bank loans to households. After accounting for household real estate assets (imposing a haircut), bank LGD would be limited to 0.51% of outstanding bank loans to households in the no-shock baseline. Only 11% of bank EAD cannot be recovered by liquidating real estate assets held by defaulting households.

However, simulations under adverse economic conditions suggest that bank losses could be much higher. The single shock with the biggest impact is a 50% decline in real estate prices, which raises the LGD ratio to more than 2%. Taken individually, the other shocks never raise the LGD above 1%. The most severe stress scenario combines several substantial shocks: a 50% drop in asset prices (real estate, bonds and stocks), a 6 percentage point increase in the unemployment rate and a 4 percentage point rise in interest rates on adjustable rate debt. This combination of shocks raises bank EAD to 9.6% of total bank loans to the resident household sector and raises LGD to 4.2% (eight times the result in the no-shock baseline). This level of losses may seem limited compared to the current level of bank capitalisation in Luxembourg, but the high-stress scenario would presumably trigger additional losses from loans to sectors not considered here, including non-resident households and non-financial corporations. In addition, mortgage lending in Luxembourg is concentrated in a limited number of important banks, so the high-stress scenario could also generate losses on interbank loans and systemic effects that are beyond the scope of this household stress test. Finally, we assume that the real estate market remains liquid even in stress scenarios.

The high-stress scenario generates substantial defaults among socio-economically disadvantaged households (i.e. those with low net wealth, low income, low education, three or more dependent children). For these different categories of disadvantaged households, the probability of default ranges from 7.7% to 14.8% and the bank losses range from 8.7% to 14.1% of their exposure to these household groups.

Our main conclusion is that bank losses appear to be quite sensitive to financial stress, despite three mitigating factors in Luxembourg. First, households hold substantial liquid assets, which allow them to continue servicing debt for several months even under stressed conditions. Second, although household leverage can be high at mortgage origination, it tends to decline rapidly among households who serviced their debt for several years. Finally, loan-to-value ratios at mortgage origination appear not to be excessive (according to households), limiting bank losses in case of default.

Abbreviations

BCL	Banque centrale du Luxembourg
CSSF	Commission de Surveillance du Secteur Financier
DA	debt-to-asset (ratio)
DSI	debt-service-to-income (ratio)
EA	euro area
EAD	exposure at default
ECB	European Central Bank
ESRB	European Systemic Risk Board
EU	European Union
FKP	financially knowledgeable person
HFCS	Household Finance and Consumption Survey
IMF	International Monetary Fund
LGD	loss given default
LTV	loan-to-value (ratio)
LU	Luxembourg
FM	financial margin
NPL	non-performing loan
PD	probability of default
ppt	percentage points
US	United States

1 Introduction

The global financial crisis demonstrated that complex links between real and financial sectors can amplify a negative shock to household balance sheets, generating severe effects for the whole economy. The resulting *"balance sheet recessions"* can be unusually persistent because many economic agents are highly leveraged at the turn of the credit cycle and need to work off their debt (Claessens et al. 2011). During the economic booms that precede such recessions, sustained economic activity and asset price appreciation encourage banks to overextend funding (Bernanke and Gertler, 1989, 1990, 1995), potentially degrading the financial resilience of both households and banks. In these conditions, a severe negative shock to households could lead to significant bank losses, with consequences spreading through the highly interconnected and leveraged financial sector to affect the whole economic system. If the banking sector is sufficiently capitalised and can rely on stable sources of funding, the system will be resilient to household shocks. However, if bank exposures to households are concentrated in few important institutions, the stress may lead to a systemic crisis.

From this perspective, several financial stability assessments for Luxembourg have called for a detailed evaluation of household resilience to economic shocks. The BCL Financial Stability Review regularly noted the steady increase in residential property prices and warned of the potential risk associated with the accumulation of household debt.[1] In addition, the BCL Financial Stability Review observed that mortgage debt is concentrated in a limited number of banks, suggesting that the household sector could be a potential source of systemic risk. In July 2016, the Luxembourg macro-prudential authority, the *Comité du Risque Systémique*, issued a recommendation that banks maintain appropriate credit standards on real estate loans.[2]

At the European level, the European Central Bank (ECB) Financial Stability Review regularly draws attention to the risks of a potential credit driven real estate bubble in Luxembourg (among other countries).[3] The European Systemic Risk Board (ESRB, 2016) also addressed a warning to Luxembourg

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1 See section 3 in the first chapter of Revue de Stabilité Financière de la BCL (2015, page 21; 2016, page 20; 2017, page 20) and the Box 1.1 in Revue de Stabilité Financière 2016 de la BCL (pages 21-23).

2 See *Avis et Recommandation du Comité du Risque Systémique* of the 1st of July 2016 (CRS/2016/004).

3 See the last paragraph of page 43 in Chapter 1 of the November 2016 ECB Financial Stability Review and Chart 1.28 on page 43 of the November 2017 ECB Financial Stability Review.

(as well as seven other EU countries) identifying medium-term vulnerabilities in the residential real estate sector.[4]

Assessments of household resilience based on aggregate data cannot properly account for differences in the distribution of debt, collateral and income across the population of households. Therefore, this paper relies instead on detailed balance sheet data at the level of individual Luxembourg households. The 2nd wave of the Luxembourg Household Finance and Consumption Survey (LU-HFCS) was collected in 2014.[5] This representative survey contains information for each household on assets (both real and financial) and liabilities (including outstanding mortgage debt), the current value of real estate collateral, as well as income and debt service flows. Results are imputed and weighted to be representative of the whole population of resident households.

We extend the study of Luxembourg household indebtedness and financial vulnerability in Giordana and Ziegelmeyer (2017) by implementing the first ever stress test of Luxembourg households. This simulates the impact of severe but plausible shocks to asset prices (real estate, bonds and stocks), household income (unemployment and cuts to social transfers or salaries) and interest rates, mapping their impact on households into bank losses. We assume that the real estate market remains liquid even in stress scenarios. Following the literature on household stress testing reviewed in section 2, we calculate a measure of households' financial margin (FM) to estimate a probability of default (PD) for each individual household. These household-level results make it possible to calculate banks' exposure at default (EAD) and loss given default (LGD) with respect to specific groups of households. The stress test is static, meaning that it does not account for second round effects, such as adjustments by households (e.g. labour supply at the extensive and intensive margin) or by banks (e.g. credit standards or terms and conditions).

Results in the no-shock baseline suggest an average PD of 3.1% across all indebted households. Aggregate bank EAD is estimated at 4.7% of household credit by multiplying outstanding loans by individual PDs and summing across the population of households. Finally, aggregate bank LGD is estimated at 0.51% of household loans, assuming that banks recover real estate assets from defaulting households and liquidate them with a haircut. Only 11% of bank exposure to defaulting households cannot be recovered using real estate assets, even after applying a haircut. This result suggests that in

4 See the ESRB warning ESRB/2016/09.
5 See Girshina et al. (2017).

the no-shock baseline household debt in Luxembourg represents only a limited source of possible bank losses.

However, stress test simulations under adverse conditions suggest that bank losses could be much higher. The shocks with the greatest impact are a 50% fall in real estate prices, which raises bank losses to 2.21% of their exposure to resident households, and a 4 percentage point increase in interest rates on adjustable rate debt, which raises bank losses to 0.89% of their exposure to resident households. We also combine shocks on income, interest rates and asset prices (real estate and liquid assets) in stress scenarios. The most severe of these scenarios results in bank losses representing 4.18% of total exposure to resident households. Compared to the loss given default in the no-shock baseline, this represents an increase by a factor of eight. The level of bank losses may still appear moderate compared to the current level of bank capitalisation[6], but this conclusion could be misleading for two reasons. First, the household stress test does not consider possible bank losses from loans to non-financial corporations or to non-resident households. Second, lending to resident households is concentrated in a few important banks, so the high-stress scenario could also generate losses on interbank loans and systemic effects that are beyond the scope of this household stress test.[7]

Socio-economically disadvantaged households suffer substantially under the most severe stress scenario. For example, on average 14.8% of households in the lowest income quintile default, which results in a LGD of 9.2% for this group.

The paper is organized as follows. The concepts behind the household stress test and the simulation methodology are explained in section 2. Section 3 provides the results for the no-shock baseline, including estimates of financial margin and liquid assets (subsection 3.1), estimates of the aggregate bank EAD and LGD ratios (subsection 3.2), as well as results under different adverse scenarios (subsection 3.3). Section 5 concludes.

[6] The Common Equity Tier 1 ratio was 23.5% for the median bank in December 2016 (see BCL, 2017, chart 3.23, page 72).

[7] See section 3 in chapter 1 of BCL Financial Stability Review (2015, page 21; 2016, page 20; 2017, page 20).

2 Methods: from household survey data to aggregate bank figures

2.1 Literature review

The literature using micro data to stress test the household sector has grown rapidly in recent years. Although studies differ in terms of scope, data and methods, some common elements are recognisable. Table 8 in Appendix A provides a systematic overview of previous studies, so we focus on a few examples in the discussion below.

Regarding the scope of the analysis, many papers focus on the impact of different economic shocks on households' financial situation, the share of financially vulnerable households or the amount of debt held by these households (e.g. Karasulu, 2008). Other papers extend the analysis to evaluate potential losses in the banking sector (e.g. IMF, 2011; Albacete and Fessler, 2010; Albacete and Lindner, 2013; Albacete et al. 2014; Gross and Población García, 2016). Our work belongs to the latter group.

Depending on their scope, studies usually follow three to four common steps. The first is to choose a rule to identify vulnerable households. The second is to define the economic shocks that will be considered. The third step involves estimating the proportion of vulnerable households under stressed conditions using the rules defined in the first step. Finally, EAD and LGD can be evaluated if sufficient data is available.

Methods mainly differ on how vulnerable households are identified. Some studies rely on respondents' self-assessment of financial distress (Martinez et al., 2013; Del Rio and Young, 2005). However, this approach cannot link the criteria defining vulnerable households to the economic shocks that could affect the household-specific financial situation.

In the absence of direct information about households' financial distress, two approaches can be distinguished. The first identifies vulnerable households as those for which one or more debt burden indicators exceeds a given threshold. This approach is implemented by Albacete and Lindner (2013) for Austria, Bricker et al. (2012) for the U.S., Djoudad (2012) and Faruqui et al. (2012) for Canada, ECB (2013) for euro area (EA) countries, IMF (2012) for Spain, and Michelangeli and Pietrunti (2014) for Italy. However, this indicator-based approach suffers from several drawbacks. First, the thresholds for the different debt burden indicators are generally set rather arbitrarily, although some recent work proposes objective criteria for this purpose (e.g. Bańbuła et al., 2016). Second, the link between household financial vulnerability and the economic shocks is often rudimentary and depends on the indicator considered. For instance, if financial vulnerability is defined using the debt-to-income ratio, then the assessment will be affected by shocks to income but not by shocks to the interest rate or to liquid assets.

The second approach relies on the concept of "financial margin", defined as the difference between a household's monthly net income and the sum of basic living costs and regular debt repayments. The main advantage of this approach is that it closely reflects bank practice when evaluating borrowers' creditworthiness. Earlier work using the financial margin follows what we call a *"binary default interpretation"*, meaning that a household has a PD of one if the financial margin is below a defined threshold (normally zero) and zero otherwise. Examples include Johansson and Persson (2006) and Riksbank (2009) for Sweden, IMF (2017) for Finland, Holló and Papp (2007) for Hungary, Albacete and Fessler (2010) and Albacete et al. (2014) for Austria, Bilston et al. (2015) for Australia, and Hlavác et al. (2012) and Galuščák et al. (2016) for the Czech Republic.

More recent studies use what we call a *"continuous default interpretation"* that accounts for differences in financial margins and liquidity buffers across households, leading to household-specific probabilities of default that can take any value between zero and one. Thus, Ampudia et al. (2016) calculate individual PDs which vary with the size of the negative financial margin and household liquid assets in 10 EA countries. This approach was recently used by Meriküll and Rõõm (2017) for Estonia and is also applied in this paper for Luxembourg.

One difficulty with the financial margin-based approach is that it requires an estimate of basic living costs. Subsection 3.1 reviews the different definitions used by the papers mentioned in this subsection. Herrala and Kauko (2007) avoid this problem by estimating an econometric model of the self-assessed level of financial distress. In the present paper, we perform a sensitivity analysis using different definitions of basic living costs.

2.2 Household financial margin and probability of default

First, we calculate a measure of the financial margin for each individual household. This compares a household's monthly disposable income to its basic living costs and regular debt repayments. We define it as follows:

$$FM_i = NI_i - DS_i - R_i - BLC_i, \tag{1}$$

where FM is the monthly financial margin for household i, NI_i is net income, obtained by adjusting gross income for taxes and social security contributions, DS_i represents current debt service, R_i is the rental charge for households that do not own their household main residence, and BLC_i is a measure of basic living costs, which can be measured in various ways as outlined in subsection 3.1.

A negative financial margin does not immediately result in a solvency problem, since we assume that households can sell their liquid assets to cover their basic living costs and to service their debt. We assume that households continue servicing their debt until they exhaust their financial assets. This assumption reflects the fact that strategic defaults are unlikely in Luxembourg, since lenders lay a claim against assets and income of a defaulting borrower (within predefined limits). Therefore, we define financially vulnerable households as those with insufficient liquid asset holdings to bridge the gap between disposable income and monthly expenses for at least M months. In theory, the minimum buffer period of M months allows vulnerable households to gain time to solve their liquidity problem and to avoid defaulting on their debt payments. However, we do not explicitly model such adjustments in our framework, simply treating M as a calibrated parameter (see subsection 3.1).

We combine the financial margin for each household with information on its liquid assets to calculate its probability of default (PD). We define the PD for household i as follows:

$$PD_i = \begin{cases} 0 & \text{if } FM_i \geq 0 \text{ or } |FM_i| \cdot M \leq LIQ_i \\ 1 - \frac{LIQ_i}{|FM_i| \cdot M} & \text{if } FM_i < 0 \text{ and } |FM_i| \cdot M > LIQ_i \end{cases} \tag{2}$$

Where LIQ_i are the liquid asset holdings of household i and M is the required number of months that a negative FM_i needs to be covered by selling liquid assets. For all households with a positive FM_i, Equation (2) sets the PD_i to zero. For households with negative FM_i, Equation (2) sets a zero PD_i if their liquid assets are sufficient to cover the negative FM_i for more than M months. For other households with negative FM_i, the PD_i is equal to one if LIQ_i holdings are zero and falls in the open interval (0,1) if liquid assets cover the negative FM_i for less than M months. Accordingly, “financially vulnerable” households are those with a PD greater than zero. Equation (2) implies that PDs will decline if the value of liquid assets increases or if the required buffer period M is shortened. Of course, a decline in PDs will reduce the share of households that are classified as financially vulnerable. Subsection 3.1 explains how M is set.

2.3 Banking sector exposure and losses: definitions

Banking sector exposure is often measured using exposure at default (EAD) and/or loss given default (LGD), but these are not defined here as in the Basel II framework. In household stress test exercises, the scale is generally set so that the outcome using the survey-based sample of households matches aggregate figures for the banking sector as a whole. Studies using the indicator-based approach or the financial margin-based approach with a *"binary default interpretation"* generally define EAD (also called debt at risk) as *"the share of total household debt held by vulnerable households"* (Riksbank, 2009, p. 52). Likewise, the LGD, also called proportion of potential loan losses, is defined as *"the proportion of [total household] debt held by vulnerable households that is not covered by household's financial or real assets"* (IMF, 2012, p. 15). Therefore, EAD and LGD provide a measure of the expected aggregate impact on the banking sector if vulnerable households were to default. In the present study we follow Ampudia et al. (2016) and adjust these definitions to account for a *"continuous default interpretation"*. Here, the EAD is obtained by weighting outstanding loans by individual household PDs and summing across the population of households. LGD is calculated by first subtracting real estate assets recovered from defaulting households (after applying a haircut) from the value of each household's outstanding loans before weighting them by individual household PDs and then summing across the population of households:

$$\boldsymbol{EAD = \sum_i PD_i \cdot D_i} \tag{3}$$

$$\boldsymbol{LGD = \sum_i PD_i \cdot (D_i - A_i)} \tag{4}$$

Where *i* indexes each indebted household in the population. Therefore, the sum of D_i over *i* represents the stock of debt in the population. The probability of default PD_i of household *i* is defined in equation (2). Finally, A_i represents the value of real estate assets that can be recovered from household *i* in case of default. The EAD and LGD ratios are defined as follows:

$$\boldsymbol{EAD\ ratio = \frac{\text{EAD}}{\sum_i D_i} = \frac{\sum_i PD_i \cdot D_i}{\sum_i D_i}}, \tag{5}$$

$$\boldsymbol{LGD\ ratio = \frac{\text{LGD}}{\sum_i D_i} = \frac{\sum_i PD_i \cdot (D_i - A_i)}{\sum_i D_i}} \tag{6}$$

2.4 Simulated shocks

We consider four shocks (a rise in interest rates, a fall in real estate prices, a decline in household income, and a fall in the value of liquid assets). These shocks are combined in two scenarios differing only in the intensity of the stress (Table 1). For each household, we calculate the impact on its financial margin and its PD from each shock in isolation as well as from the combination of shocks in the stress scenarios. These affect the share of households that are classified as financially vulnerable (PD>0).

The simulated shocks affect the financial margin, PD, EAD and LGD in different ways. Declines in household income (whether imposed uniformly across households or via an unemployment shock) affect the financial margin directly, as do interest rate increases (via debt payments). Declines in liquid assets reduce the number of months that a household can cover a negative financial margin. Therefore, these three shocks increase household PDs, raising the share of financially vulnerable households and therefore the EAD over the population as a whole. The fall in real estate prices reduces the value of collateral and therefore increases the LGD.

Interest rate increase: Mortgage rates are currently at historically low levels. According to the forward guidance provided by the ECB Governing Council, it expects policy rates *"to remain at their present levels for an extended period of time, and well past the horizon of our net asset purchases"* which are intended to run until the end of September 2018. However, this position may be reassessed if the cyclical recovery produces a sustained adjustment in the path of inflation consistent with Governing Council's aim. Abroad, the US Federal Reserve and the Bank of England have already begun to raise interest rates. In addition, while EA policy rates may remain at current levels, sovereign bond yields could rise following a confidence shock, with a likely impact on long-term mortgage rates.

We consider interest rate increases of 1, 2, 3 or 4 percentage points (ppt)[8]. Each household faces an additional monthly interest payment equal to its outstanding amount of adjustable rate loans multiplied by the interest rate increase and divided by 12.[9] We add this to the reported household

8 In a similar exercise for Spain, IMF (2012) considered 1, 2 and 3 ppt increases. We add the 4 ppt increase to allow for the current historically low level of interest rates. However, such a large rise would be unlikely over the 3 to 12-month horizon relevant for our static simulations.

9 According to the 2014 LU-HFCS, 70% of total outstanding household debt is at adjustable rates compared to 79% in 2010/2011. This information is only collected for the two most important mortgages in each household. For other mortgages, we assume that the same share of debt is at adjustable rates. Outstanding balances on credit lines/overdrafts or credit card debt is assumed to be at adjustable rates. Other non-mortgage debt (e.g. consumer loans and private loans) is assumed to be at fixed rates.

debt service (DS) in equation (1), reducing the household's financial margin and therefore raising its PD.[10]

Household income/unemployment shock: First, we follow IMF (2012) in implementing a uniform reduction of household income by 5%, 10% or 20%. This might reflect a nominal wage cut in a crisis. A uniform shock represents a rather extreme case because we apply it to all household members, although wage cuts may differ across sectors of production and risk sharing is common within households.

Second, to allow for the heterogenous nature of households, we consider the impact of an unemployment shock on household income. We simulate increases of 2, 4 and 6 ppt in the probability that the *"financially knowledgeable person"* (FKP) of each household becomes unemployed. These increases are comparable to those experienced by Greece, Spain and Ireland during the crisis. Following Albacete and Fessler (2010), we implement this shock by estimating a logit model for the employment status of FKPs between 20 and 64 years of age using both waves of the survey to increase the number of observations (a year dummy is included). The vector of explanatory variables includes individual characteristics of the FKP such as gender, age, country of birth, marital status, highest educational attainment, as well as other household characteristics such as household size, homeowner/tenant status, household gross income and net wealth (see Table 4). We use the estimated logit coefficients to predict the probability of becoming unemployed for each individual FKP. The shock to the unemployment rate is implemented by adding 2, 4 or 6 ppt to the estimated constant. For each FKP, we draw a random real number from a uniform distribution over the interval (0,1) and assume a transition to unemployment if this number is below the individual's predicted probability of being unemployed. In this case, household income is adjusted according to unemployment benefit regulations in Luxembourg (see below). The estimates of the PD, EAD and LGD reported below are averages across 1000 Monte Carlo iterations of this process.

In Luxembourg, unemployment benefits cover 80% of previous salary. However, during the first 6 months they cannot exceed 2.5 times the minimum wage[11] and for the following 6 months they cannot

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10 The Luxembourg government provides subsidies to some households with mortgages on their main residence. The amount depends on household income and family situation. The Ministère du logement provides additional details in its 2016 annual report (p.22). The impact of an interest rate increase on debt service is unaffected by mortgage subsidies. However, the income or unemployment shock could increase the number of households eligible for the subsidy, as well as its size. We do not take this into account.

11 In 2014, the gross social minimum wage was €2,305 for the skilled and €1,921 for the unskilled.

exceed 2.0 times the minimum wage.[12] For each of the three unemployment shocks (2, 4 or 6 ppt increase in probability of unemployment), we focus on the more extreme case, applying the 2.0 threshold on benefits.

Fall in liquid assets: From equation (2), the amount of liquid assets available for sale determines the PD. Following Ampudia et al. (2016) we define liquid assets as the sum of the following: deposits (mainly sight and saving accounts), stocks (publicly traded stocks, mutual funds predominantly investing in equity, managed accounts, hedge funds), bonds (bonds and funds predominantly investing in bonds), and potentially less liquid assets (value of private businesses other than self-employment and other assets[13]). We assume that "stocks" and "bonds"[14] decline in value by 10% to 50% and that "less liquid assets" lose 20% to 100% of their value. Deposits are unaffected (we assume that there are no bank failures). To the best of our knowledge, other studies do not consider a fall in liquid assets.

Fall in real estate prices: Following the global financial crisis, several European countries, including Ireland, Cyprus, Greece, the Netherlands and Spain, experienced sharp reductions in real estate prices. For instance, according to the residential property price index published by the ECB, the price of new and existing dwellings declined by 53% in Ireland between the peak in 2007 and the trough in 2012. In Greece, the price of new and existing flats declined by 40% between 2008 and 2015.

We consider five different shocks to the nominal price of real estate. Declines are assumed to be identical across different types of real estate (houses, apartments, non-residential properties) and different regions within Luxembourg. Following a similar IMF (2012) exercise for Spain, we consider falls of 10%, 20% and 30%[15]. In addition, we consider two more extreme declines of 40% and 50%. The most severe shock, a 50% price decline, would completely offset the observed appreciation of residential property prices between 2002 and 2014. Note that in Ireland it took approximately five years for property prices to decline by this percentage, while in our stress test the decline would be immediate. In our simulations, property price declines reduce the value of collateral and affect the LGD as indicated in equation (4).[16] For banks recovering collateral from defaulting households, we

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[12] See *Code du Travail, Titre II, Chapitre 1, section 7,* p. 269*.*

[13] This includes assets such as options, futures, index certificates, precious metals, oil and gas leases, future proceeds from a lawsuit or estate that is being settled, and royalties.

[14] The LU-HFCS does not distinguish bonds issued by governments, by financial intermediaries or by non-financial corporations. Only the total amount invested in bonds in known.

[15] IMF (2012, table 2, p. 16) provides an overview of shocks applied in several studies.

[16] These shocks could also affect the value of real estate investment funds, but these represent less than 1% of

apply an additional haircut of 25% to the shocked value of real estate assets (see subsection 3.2). We assume that the real estate market remains liquid even in stress scenarios.

Stress scenarios: we combine several individual shocks in a medium-stress scenario and a high-stress scenario (Table 1). The shock to income is implemented via a rise in the unemployment rate. In designing these scenarios we focus on extreme shocks associated with "tail risk" (e.g. EU fragmentation, trade war, nuclear accident close to Luxembourg) that would generate a systemic crisis. We do not consider this combination of shocks particularly likely, but stress tests are designed to focus on extreme events. It may be puzzling that we consider an increase in interest rates, which one may expect to fall during a crisis. However, Luxembourg is a very small economy within the European Monetary Union, where interest rates are set for the euro area as a whole, so it is quite plausible that monetary policy does not react to local conditions. Even if domestic conditions reflected some euro area developments, a simultaneous increase in interest rates and unemployment could be consistent with a negative supply shock, which would move output and prices in opposite directions.

Table 1 : Definition of stress scenarios

Stress scenario	Interest rates	Real estate asset prices	Other asset prices (Stocks, bonds, less liquid assets)	Unemployment rate
Medium	+ 2 ppt	- 30%	- 30%, -30%, -60%	+ 4 ppt
High	+ 4 ppt	- 50%	- 50%, -50%, -100%	+ 6 ppt

It is difficult to compare our scenarios to others in the literature. In particular, our stress scenarios differ from those in Meriküll and Rõõm (2017), which are designed to mimic the Great Recession and therefore envisage a fall in interest rates. Albacete et al. (2014) also focuses on 2009, comparing alternative growth scenarios. Ampudia et al. (2016) combine a 3 ppt increase in interest rates, a 2 standard deviation reduction of real estate prices (this would be a 22.4% reduction in Luxembourg) and a 2 standard deviation increase of the unemployment rate (a 1.54 ppt increase in Luxembourg). Their stress scenario is partly less demanding (no fall in asset prices other than real estate) and partly more demanding than the medium-stress scenario in Table 1. Compared to our high-stress scenario, it is less demanding along all dimensions. Ampudia et al. apply their scenario to several EA countries.

household mutual funds holdings in 2014 (LU-HFCS). In addition, real estate funds are likely to be internationally diversified rather than focused on Luxembourg.

3 Results

Results are based on a sample of 1601 households from the 2nd wave of the Luxembourg Household Finance and Consumption Survey (LU-HFCS). Interviewed households are weighted depending on their characteristics to obtain representative results for the entire population of households resident in Luxembourg. Although the survey took place in 2014, it provides the most recent micro dataset available for household stress testing. For the stress-test exercise, the reference population is limited to indebted households only, meaning those who hold mortgage debt (on the household main residence or on other real estate property[17]) or non-mortgage debt (including outstanding balances on credit lines/overdrafts and credit card debt, as well as consumer and private loans). Indebted households represent 54.6% of the households in the sample or 952 unweighted observations.

We start by calculating the financial margin for each indebted household in the sample. Each household's Probability of Default is calculated by combining information on its financial margin and its liquid assets. We estimate bank exposure at default by summing outstanding loans across households using individual PDs as weights. Bank loss given default is calculated by assuming that banks liquidate real estate assets recovered from defaulting households (applying a haircut). Finally, we perform the stress test by repeating this exercise under stressed conditions.

3.1 Financial margin and liquid assets

To calculate the financial margin defined in equation (1) we proceed as follows. First, net income (NI) is provided by each household in LU-HFCS.[18] Second, debt service is also set to the value reported by each household in answering the standard HFCS questionnaire. This includes both interest and capital repayments on mortgage and non-mortgage debt. Third, the rental charge (R) on the household main residence is also taken from the standard questionnaire (for owner-occupiers this is zero).[19]

There are various ways to estimate basic living costs (BLC in equation 1). Several studies assume the same value for all households. For instance, Ampudia et al. (2016) use the poverty line definition of the European Commission, setting basic living costs at 40% of median income. Meriküll and Rõõm (2017) use an official estimate of the subsistence minimum provided by Statistics Estonia. Other

[17] Including any non-residential real estate.

[18] We use the same definition as Albacete et al. (2014) and Albacete and Lindner (2013). Ampudia et al. (2016) used gross income adjusted with an estimate of taxes but did not consider social security contributions.

[19] Rental charges are considered by Albacete et al. (2014) but not by Ampudia et al. (2016).

studies estimate basic living costs on an individual household level by using external data sources (Johansson and Persson, 2006; Albacete and Fessler, 2010[20]), other household data in the available sample (Bilston et al., 2015)[21] or direct self-reported measures of consumption (Galuščák et al., 2016)[22].

We propose four alternative measures for basic living costs. Our first measure includes amounts spent on utilities[23] and on food consumed at home, as well as 50% of the amounts spent on food outside the home. In addition to FM 1, our household-specific measure of the financial margin, we also use three measures that set basic living costs at a common value for all households: FM 2 uses the median of the household-specific measure, FM 3 uses the median of disposable income within the lowest quintile of disposable income and FM 4 uses 60% of the median amount spent on consumer goods and services.[24] Table 2 provides summary statistics for each of the four alternative measures of financial margin, which only differ in the definition of basic living costs.

Table 2 : Statistics on the financial margin (FM) for indebted households

Financial margin (FM)	Mean	Median	% of households with FM<0	Households with neg. FM Mean	Households with neg. FM Median
FM 1: Food & utilities (individual)	3,099 €	2,347 €	11.0%	-139 €	-622 €
FM 2: Food & utilities (median)	3,301 €	2,451 €	11.6%	-134 €	-685 €
FM 3: Net income (median in quintile 1)	3,382 €	2,532 €	11.1%	-125 €	-647 €
FM 4: Consumption of goods & services (60% of median)	3,365 €	2,515 €	11.1%	-127 €	-662 €

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

The mean monthly financial margin of indebted households ranges from €3,099 to €3,382 depending on the definition (Table 2). Given the well-known asymmetry of the income distribution, it is not surprising that the median is lower than the mean and ranges from €2,347 to €2,532.[25] This means

[20] These authors use EU-SILC 2008 data to estimate the relationship between household characteristics and basic living costs. Estimated coefficients serve to predict household specific basic living costs. As a robustness check, they use minimum social benefits paid to single-person households in Vienna.

[21] For each household they estimate minimum consumption expenditure based on household characteristics and actual consumption reported in the survey.

[22] They use the sum of food, energy, health and rent expenditures as reported in their household level data.

[23] Survey question: *"About how much does your household spend on utilities (e.g., electricity, water, gas, telephone...) in a typical month?"*

[24] Survey question: *"So overall, about how much does your household spend in a typical month on all consumer goods and services? Consider all household expenses including food, utilities, etc. but excluding consumer durables (e.g. cars, household appliances, etc.), rent, loan repayments, insurance policies, renovation, etc."*

[25] The expenses we subtract from net income average between €2500 and €2800 per household (including debt service). This is consistent with a recent Statec report (Franziskus, 2017) that estimates a basic budget for couples of €2600 including accommodation costs.

that most indebted households have more than €2,000 per month at their disposal after deducting debt service charges, rent and basic living costs. Between 11.0% and 11.6% of all indebted households have a negative financial margin. On average, this deficit is between €125 and €139 per month. The median deficit ranges between €622 and €685.

We conclude from Table 2 that the alternative definitions of the financial margin do not make much of a difference. Below we focus on FM 1, which uses the household-specific measure of basic living costs. The three measures that employ a common level of basic living costs for all households are used to test the robustness of our results and are reported in the Annex. Results of the stress test are similar across all measures of the financial margin, so our conclusions are unaffected.

Table 3 reports liquid asset holdings across all indebted households. These average €100,302 although the median is substantially lower at €15,760. Indebted households with a negative financial margin have lower liquid assets: their mean is €51,055 and their median is €4,380. Table 3 also indicates the share of households who cannot cover their negative financial margin over a given number of months by liquidating their assets. Among indebted households with negative financial margin, 4.9% have no liquid assets at all (column "No liquid assets"). These households have a PD of one. In the following column and the same row, 25.1% of indebted households with a negative financial margin do not have enough liquid assets to cover it for a full month. The share increases to 38.7% if liquid assets must cover the negative financial margin for three months. It increases further to 56.2% if they have to fill the gap for a year. However, this share falls to only 6.2% if we consider all indebted households (not just those with a negative financial margin). The bottom row of Table 3 reports the increase in the average PD across all indebted households as the required number of months is extended.

For the purposes of the stress test, we follow Meriküll and Rõõm (2017) and Ampudia et al. (2016) in setting the required number of months M so that the ratio of EAD to total household loans in our micro data matches the ratio of non-performing loans (NPLs) to total loans to households in the aggregate data for the whole banking sector (2014Q4). The latter ratio is calculated from bank prudential reports to the *Commission de Surveillance du Secteur Financier* (CSSF). However, 2014 data on NPLs was not disaggregated by economic sector, so we scale it by the share of loans to the household sector using data collected by the BCL. This suggests that NPLs make up 4.45% of Luxembourg bank lending to the household sector[26]. We set M to three months since this provides the best fit to a NPL ratio of 4.45%.

[26] The NPL ratio falls to 2.1% if we consider lending to resident households only. More reliable data on NPLs

In addition, three months happens to match the 90 day limit conventionally used to define NPLs in the International Financial Reporting Standards (IFRS).

Table 3: Summary statistics on liquid assets and share of households with insufficient liquid assets to cover their negative financial margin (FM) for the indicated number of months

	Liquid assets (LIQ)		Share of households with insufficient liquid assets to cover negative FM for the indicated number of months					
	Mean	**Median**	**No liquid assets**	**1**	**2**	**3**	**6**	**12**
All indebted households	100,302 €	15,760 €	0.5%	2.7%	3.6%	4.2%	5.4%	6.2%
Indebted households with neg. FM	51,055 €	4,380 €	4.9%	25.1%	33.2%	38.7%	49.4%	56.2%
			Average PD					
			No liquid assets	**1**	**2**	**3**	**6**	**12**
All indebted households	100,302 €	15,760 €	0.5%	2.1%	2.7%	3.1%	4.0%	4.9%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities). Appendix B Table 9 provides this table with all four definitions of the FM.

3.2 Probability of default, exposure at default and loss given default

At the level of the individual household, we combine the PD with information on individual real assets and liabilities to calculate the EAD and LGD. Aggregating across households, we can then move from the survey-based evaluation to aggregate figures for the banking sector as a whole. In the following we focus on the no-shock baseline. Results for the adverse scenarios are discussed in subsection 3.3.

In order to calculate LGD as defined in equation (4), we assume that when a household defaults banks can only recover real estate assets. Real estate assets include not only the household main residence but also other real estate property. We apply a haircut of 25% to the reported value of real estate assets, representing transaction costs in liquidation and further drops in prices if forced sales materialise. Our haircut falls between the 27% estimate by Campbell, Giglio and Pathak (2011) in Massachusetts (US) and the 20% used by Ampudia et al. (2016).[27]

Table 4 reports estimates of the mean value for the PD, EAD and LGD for different groups of indebted households in 2014. In the top row (all indebted households), the mean PD is 3.1% and the mean EAD

disaggregated by economic sector only became available recently. In September 2016, the NPL ratio for resident households was 1.5%. For the purposes of the stress test, we prefer to use the more conservative figure of 4.45%.

[27] Based on individual real estate transactions in Luxembourg (2007-2016) apartments sold at auction are on average around 15% below their standard selling value and houses are about 11% below. However, the number of auctions is very limited (data does not identify foreclosures and includes voluntary auctions).

ratio is 4.7%. Given that most vulnerable households own some real estate assets, the LGD ratio in this row is only 0.51%, even after applying a haircut of 25%. This means that only 11% (=0.51/4.7) of exposure at default is not covered by sufficient real estate assets.

Table 4 also reports the PD, the EAD ratio and LGD ratio for specific groups of households. As expected, PD, EAD ratio and LGD ratio vary considerably depending on household characteristics. In general, disadvantaged households are associated with higher PDs and therefore higher EAD and LGD ratios. However, this does not necessarily translate into a substantial level of credit risk because these households tend to hold a smaller share of the overall debt.[28] For instance, households with three or more dependent children, generally considered a socially vulnerable group, have a higher PD, and therefore higher EAD and LGD ratios than households with fewer children. However, this group represents less than ten percent of total debt (see central panel). A similar pattern appears when grouping by other household characteristics (e.g. education level, employment status, housing status, net wealth).

Methodological and data differences complicate the comparison with other results in the literature on household stress testing (none of which consider Luxembourg). Among the most similar studies, Ampudia et al. (2016) use the first wave of the HFCS to estimate EAD ratios for 10 different countries (excluding Luxembourg). These range from 3.5% in France to 9.3% in Greece with an average of 4.4% (Table 6 on their page 9). Thus, our 4.7% estimate for Luxembourg's EAD ratio in 2014 is close to their country average in 2010/2011. To calculate Loss Given Default, Ampudia et al. (2016) assume that banks can recover liquid assets as well as real estate assets (with no haircut). They find an LGD ratio ranging from 0.36% for Belgium to 2.46% for Greece. Thus, our 0.51% estimate of the average LGD ratio in Luxembourg (in 2014) is substantially below their cross-country average of 1.12%, but still within their range.

For Estonia, Meriküll and Rõõm (2017) estimate an EAD ratio of 3.4% and a LGD ratio of 0.4% (using their reference definition), which is slightly below our estimates for Luxembourg. They limited the required number of months to one (actually 30 days) to match their EAD ratio to the observed share of NPLs in total loans to households for the whole banking sector.

[28] Giordana and Ziegelmeyer (2017) make a similar point.

Table 4 : PD, EAD and LGD for different groups of indebted households (no-shock baseline)

Variable name	Variable label	Mean net wealth	Mean net income	Debt in Million €	Share of total debt in %	Mean PD in %	EAD in % of Debt	LGD in % of Debt
Total	Total	812,462 €	70,649 €	20,530 €	100.0	3.1	4.7	0.51
Gender	Male	839,865 €	74,806 €	12,264 €	59.7	3.2	5.8	0.75
	Female	775,154 €	64,989 €	8,266 €	40.3	2.8	3.2	0.15
Age classes*	16-34	323,977 €	54,920 €	5,714 €	27.8	2.1	2.1	0.08
	35-44	555,793 €	74,521 €	7,213 €	35.1	3.1	2.4	0.54
	45-54	1,067,256 €	80,540 €	4,890 €	23.8	2.2	5.5	1.12
	55-64	1,354,852 €	76,298 €	2,139 €	10.4	6.3	18.3	0.17
	65+	1,063,735 €	55,632 €	574 €	2.8	1.4	3.5	0.38
Country of birth*	Luxembourg	945,015 €	73,196 €	12,535 €	61.1	2.6	5.4	0.61
	Portugal	279,347 €	46,717 €	1,967 €	9.6	4.6	4.6	0.86
	France	1,107,487 €	83,139 €	1,915 €	9.3	0.5	0.3	0.00
	Belgium	815,307 €	95,640 €	878 €	4.3	1.9	0.3	0.32
	Italy	578,545 €	70,149 €	477 €	2.3	5.8	0.7	0.49
	Germany	747,000 €	63,444 €	879 €	4.3	8.1	20.8	0.00
	Other countries	596,383 €	67,508 €	1,878 €	9.1	3.8	0.3	0.28
Household size	1 member	470,625 €	44,463 €	3,729 €	18.2	2.7	6.7	0.08
	2 members	972,799 €	74,817 €	5,158 €	25.1	2.6	5.3	1.05
	3 members	1,163,979 €	77,976 €	4,125 €	20.1	3.5	1.3	0.21
	4 members	760,929 €	79,484 €	4,966 €	24.2	1.8	2.4	0.44
	5+ members	694,781 €	88,619 €	2,552 €	12.4	6.2	10.7	0.67
Number of dependent children	no children	897,302 €	64,100 €	9,367 €	45.6	2.2	5.2	0.61
	1 child	806,438 €	77,466 €	4,666 €	22.7	3.8	1.7	0.15
	2 children	665,031 €	76,149 €	4,499 €	21.9	3.0	3.6	0.55
	3+ children	629,762 €	83,738 €	1,999 €	9.7	7.0	11.9	0.79
Marital status*	Single	510,700 €	59,661 €	5,157 €	25.1	3.0	5.2	0.08
	Couple	961,429 €	80,072 €	12,739 €	62.0	2.9	4.0	0.73
	Divorced	778,002 €	58,444 €	2,512 €	12.2	4.5	7.8	0.29
	Widowed	809,526 €	53,829 €	123 €	0.6	1.0	1.0	0.00
Education level*	Low (ISCED=0,1,2)	377,571 €	50,957 €	3,042 €	14.8	4.3	8.0	2.28
	Middle (ISCED=3,4)	753,557 €	65,410 €	7,353 €	35.8	3.8	8.3	0.16
	High (ISCED=5,6)	1,144,270 €	88,573 €	10,136 €	49.4	1.5	1.1	0.23
Employment status*	Employed	670,250 €	71,197 €	15,704 €	76.5	2.4	2.8	0.11
	Self-Employed	1,647,558 €	117,853 €	2,164 €	10.5	1.7	4.4	0.78
	Unemployed	344,842 €	47,145 €	203 €	1.0	7.2	4.4	0.66
	Retired	1,366,964 €	62,213 €	1,485 €	7.2	4.4	16.0	0.30
	Other not working	802,899 €	58,736 €	1,064 €	5.2	6.2	17.4	5.99
Housing status	Owner-outright	1,621,510 €	83,275 €	1,845 €	9.0	0.4	0.6	0.00
	Owner-with mortgage	785,313 €	75,159 €	16,439 €	80.1	2.6	4.6	0.53
	Renter or other	226,944 €	51,421 €	2,246 €	10.9	6.1	8.8	0.77
Total gross income	Quintile 1	304,939 €	24,491 €	2,233 €	10.9	9.3	12.6	1.22
	Quintile 2	351,549 €	43,744 €	3,112 €	15.2	3.1	9.0	0.28
	Quintile 3	544,103 €	58,692 €	3,625 €	17.7	1.5	4.2	1.45
	Quintile 4	775,232 €	80,610 €	4,572 €	22.3	1.4	4.4	0.00
	Quintile 5	2,095,807 €	146,433 €	6,988 €	34.0	0.1	0.7	0.23
Total net wealth	Quintile 1	-3,423 €	41,482 €	2,651 €	12.9	8.2	8.0	3.28
	Quintile 2	186,395 €	52,988 €	4,892 €	23.8	4.2	7.1	0.34
	Quintile 3	424,987 €	62,459 €	3,938 €	19.2	0.6	0.5	0.02
	Quintile 4	748,436 €	78,042 €	3,843 €	18.7	1.9	8.5	0.00
	Quintile 5	2,721,683 €	118,684 €	5,206 €	25.4	0.5	1.2	0.00

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities). Appendix B Table 10 provides this table with all four definitions of the FM. The quintiles for total gross income and total net wealth are adjusted to indebted households. Personal characteristics refer to the "financially knowledgeable person" (FKP) indicated by an asterisk.

Compared to Meriküll and Rõõm (2017) and to Ampudia et al. (2016), our approach differs in four dimensions. First, we apply a higher haircut to liquidated real estate assets. Second, we have a more restrictive definition of household assets that can be liquidated in case of default. Third, we use a period of 3 months over which a negative financial margin needs to be covered by selling liquid assets. This is a prudent estimation for Luxembourg (see footnote 26), raising our estimates of the household-specific PD. Finally, there are also differences in the measures of basic living costs. Overall, our design is more conservative.

Comparability to other studies is more limited because of larger differences in methods as well as data. Albacete and Lindner (2013) use the 1st wave of the Austrian HFCS but they identify financially vulnerable households using several different conditions: debt-to-asset ratio (DA) of 75% or more, debt service-to-income ratio (DSI) of 40% or more, expenses exceeding income, and inability to meet expenses. They assume that all vulnerable households default on their debt, leading to substantially higher EAD and LGD ratios. Thus, for DA≥75% the EAD ratio is 29.3% and the LGD ratio is 10.2%. For DSI≥40%, the EAD ratio is 11.9% and the LGD ratio is 2.8%.

Using the same dataset, Albacete et al. (2014) identify vulnerable households using the financial margin, as in Ampudia et al. (2016) or the present paper. However, they simply assume that a negative financial margin is enough for a household to default, without accounting for the availability of liquid assets. Overall, their estimated LGD ratio is almost 5%.

IMF (2012) uses a Spanish household survey conducted in 2008 and defines financially vulnerable households as those with a debt service-to-income ratio of 40% or above. Again, no haircut is applied to real estate assets, yielding an EAD ratio of 45.6% and a LGD ratio of 1.1%. More recently, IMF (2017) used a 2009 Finnish household survey, applying a concept analogous to the financial margin (the 'net income margin') and estimating an average PD of 2.2%.

3.3 Simulations

This subsection presents the results of simulated shocks. Table 5 shows the impact on the mean PD, the EAD and the LGD from the shocks defined in subsection 2.4. The first row reports these figures from the no-shock baseline, the middle panel reports the estimate for each shock considered separately and the bottom panel reports the estimate when several shocks are combined in the medium- and high-stress scenarios.

Table 5: Stress test results for all indebted households

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	LGD/EAD in %
	No-shock baseline		3.1%	4.7%	0.51%	10.8%
Individual shocks	Income	-5%	3.2%	4.9%	0.53%	10.7%
		-10%	3.4%	5.2%	0.54%	10.5%
		-20%	3.9%	5.9%	0.66%	11.2%
	Unemployment	+2 ppt	3.2%	4.9%	0.53%	10.9%
		+4 ppt	3.2%	5.0%	0.54%	10.9%
		+6 ppt	3.2%	5.1%	0.55%	10.9%
	Interest rate	+1 ppt	3.2%	5.2%	0.53%	10.1%
		+2 ppt	3.3%	5.8%	0.62%	10.6%
		+3 ppt	3.4%	6.3%	0.75%	12.0%
		+4 ppt	3.6%	6.8%	0.89%	13.1%
	Liquid assets (stocks and bonds; less liquid assets)	-10%; -20%	3.1%	4.7%	0.51%	10.8%
		-20%; -40%	3.1%	4.7%	0.51%	10.8%
		-30%; -60%	3.1%	4.7%	0.51%	10.8%
		-40%; -80%	3.1%	4.7%	0.51%	10.8%
		-50%; -100%	3.1%	4.7%	0.51%	10.7%
		-100%; -100%	3.3%	4.8%	0.52%	10.7%
	Real estate	-10%	3.1%	4.7%	0.71%	15.0%
		-20%	3.1%	4.7%	0.99%	21.1%
		-30%	3.1%	4.7%	1.37%	29.0%
		-40%	3.1%	4.7%	1.76%	37.2%
		-50%	3.1%	4.7%	2.21%	46.8%
Combined shocks	Combined using income shock	medium	3.7%	6.4%	1.86%	29.1%
		high	5.3%	9.3%	4.05%	43.4%
	Combined using unempl. shock	medium	4.0%	6.7%	1.83%	27.1%
		high	5.3%	9.6%	4.18%	43.4%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities). Corresponding tables for the other definitions of the FM appear in Appendix B (Table 11, Table 12, and Table 13).

3.3.1 Income and unemployment shocks

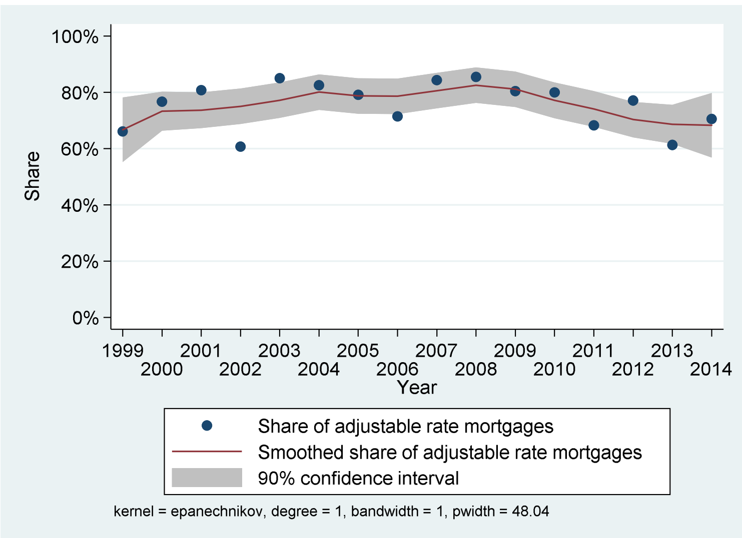
Income and unemployment shocks have a rather limited impact on the mean PD, the EAD ratio and the LGD ratio (Table 5). Regarding the unemployment shock, the most severe (6 ppt) increase in the unemployment rate results in a 0.04 ppt increase in the LGD ratio compared to the no-shock baseline. The mean PD increases by 0.1 ppt and the EAD ratio by 0.4 ppt. The uniform 20% reduction in total household income generates the strongest impact. This is not surprising since it affects all households, unlike the unemployment shock. However, the 5% and 10% reductions in income have effects similar to those of the unemployment shocks.

Two factors may explain the apparent resilience of households to income shocks. On the one hand, households hold substantial liquid assets, allowing them to continue financing their expenditure for several months even if their income declines. On the other hand, the debt service-to-income ratio is usually modest in Luxembourg, with a median value around 15% for total debt and 18% for mortgage loans (see Table 2 in Giordana and Ziegelmeyer, 2017). This may reflect household income growing since the date of debt origination, repayments of part of the debt, or declines in interest rates. In fact, we find that the median debt service-to-income ratio is higher for recent buyers (five years or less since date of acquisition), although at 22% it may still allow a sufficient margin to absorb income shocks.

3.3.2 Interest rate shock

Although the interest rate shock has a limited impact on the mean PD, it has a substantial impact on the EAD ratio (raising it to 6.8% for the most severe shock) and the LGD ratio (raising it to 0.89%). This is puzzling at first sight, given that the interest rate shock targets a narrower population (adjustable rate debt represents about 70% of total household debt outstanding; see Figure 1)[29]. However, the income shock has a uniform impact across households regardless of their debt level, while the interest rate shock will have a greater effect on more leveraged households. In fact, households with adjustable rate debt and a debt-to-income ratio above 5 suffer a bigger reduction in their financial margin from a 4 ppt increase in the interest rate than from a 20% reduction of their income. As a result, even if the average PD is less affected, there are more pronounced effects on EAD and LGD.

Figure 1: Share of adjustable rate mortgages by year of origination



Notes: Results are imputed and weighted. The smoothed line and confidence intervals are estimated using Kernel-weighted local polynomial smoothing (Stata manual 13, command lpoly). The year 1999 summarizes all years from 1983-1999.

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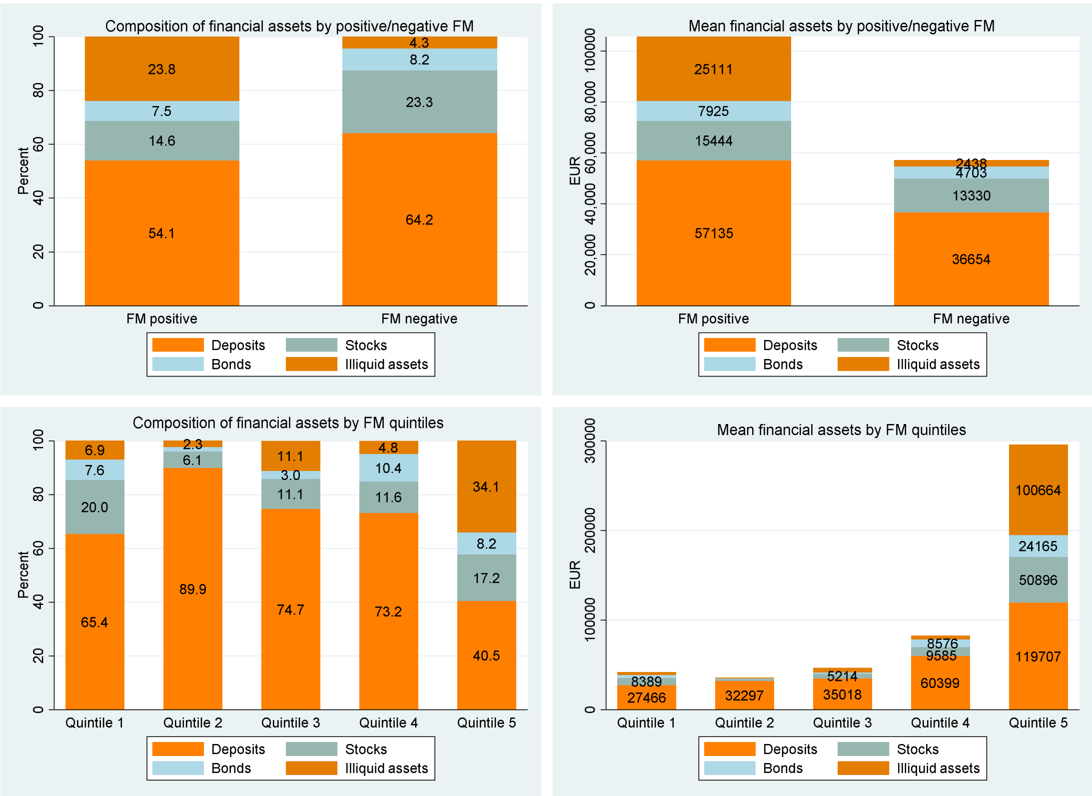
29 Figure 1 refers to the **stock** of outstanding debt. The share of adjustable rate mortgages in the **flow** of new mortgages has fallen rapidly since 2014 (see BCL 2017 *Revue de stabilité financière*, figure 1.9 page 24).

3.3.3 Liquid asset shock

The simulated decline in the value of liquid assets, even in the most severe case, has no visible impact on the mean PD or on the EAD and LGD ratios. This can be explained by the large share of insured deposits in the composition of liquid assets. In the upper left panel of Figure 2, deposits make up around 64% of liquid assets among households with a negative financial margin. For these households, illiquid financial assets represent only slightly more than 4% of their portfolio, while stocks and bonds account for less than 32%. Thus, it appears that the volume of deposits held by households with a negative financial margin comfortably exceeds their expenditure needs. In fact, these households hold an average of €36,000 in deposits (upper right panel of Figure 2) while their average negative financial margin is only €139 per month (Table 2). As insured deposits[30] are unaffected by the liquid asset shock, average PD will only be marginally affected and the EAD and LGD ratios are virtually unchanged.

Figure 2: Financial assets of indebted households according to their financial margin (FM)



Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities).The quintiles for the FM refer to the population of indebted households only.

30 In Luxembourg, eligible deposits are insured up to 100,000 euros per person and per bank.

Note that the liquid asset shock would more strongly affect households with a more positive financial margin (see bottom panel of Figure 2 for the composition of liquid assets held by households in the top financial margin quintiles). Since most of these households have a positive financial margin, their PD will remain zero and the simulation results will be unaffected.

3.3.4 Real estate shock

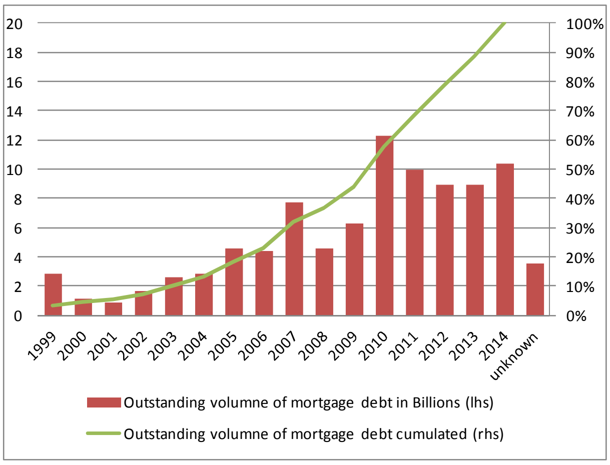
By construction, a fall in real estate prices does not affect the mean PD or the EAD ratio but only affects the LGD ratio, as it reduces the value of collateral that banks recover from defaulting households. Naturally, a 50% drop in real estate prices has the biggest impact on the LGD ratio, which rises to more than 2%, exceeding the impact of any other single shock. In the no-shock baseline only 11% of EAD is not covered by real estate assets. Following a 50% decline in real estate prices, this share increases to 47%.[31] It may be puzzling that the impact on the LGD ratio appears to be rather low. We consider three possible explanations below.

First, collateral values are high because Luxembourg property prices have grown substantially over two decades. The cumulated increase in prices since the year of mortgage origination partially compensates for the simulated decline in real estate prices, especially for households who bought several years ago. Given the historical experience of rising property prices in Luxembourg, a 50% decline would only return the average property price from its 2014 level to its 2002 level. In 2014, 7% of the outstanding mortgage debt originated before 2002 (Figure 3, green line)[32]. For these mortgage loans, even the original amount (not just the outstanding amount) could be fully reimbursed from the value of real estate collateral even after a 50% decline in property values. The situation is less rosy for the remaining 93% of mortgage debt, but the increase in property prices since the year of purchase still mitigates the impact of a fall in collateral values.

31 We assume an additional 25% haircut when liquidating real estate assets (on top of the simulated drop).

32 The year of take out is unknown for 3.9% of the total outstanding mortgage debt since households were only asked the year of take out for their two most important mortgages.

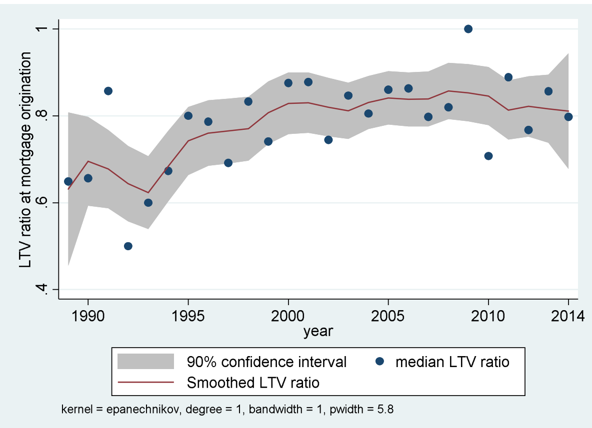
Figure 3: Outstanding volume of mortgage debt in 2014 by year of origination

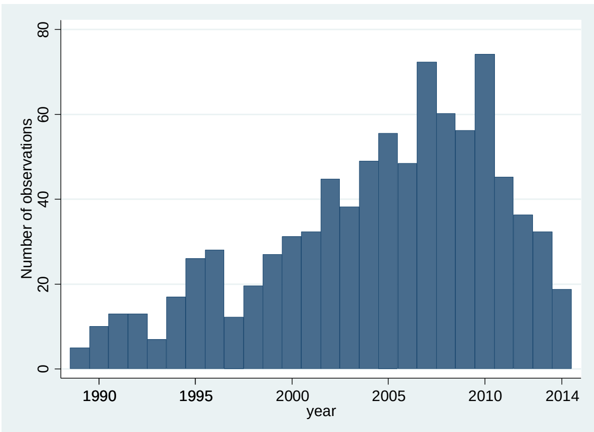


Source: Own calculations based on the 2nd wave of the LU-HFCS. Results are imputed and weighted.
Note: Mortgages include those for the purchase of the household main residence or other real estate property. The cumulated share does not account for mortgages with unknown year of origination.

Second, most mortgages do not cover the whole value of the property at acquisition. The loan-to-value (LTV) ratio at origination is 84% according to the median estimate from the 1st wave of the HFCS (BCL, 2013) and 78% for the 2nd wave. Figure 4 reports the median LTV ratio across households with mortgages originating in each year since 1989. This stabilised around 80% from 2000 onwards. The values are smoothed across years, given the low number of observations for certain years, in particular at the beginning and the end of our sample. The right-hand panel illustrates the unweighted number of outstanding mortgages in our sample that were originated in each year up to 2014.

Figure 4: Loan-to-Value Ratio at mortgage origination in Luxembourg 1989-2014 (left panel) and number of observations per year (right panel)

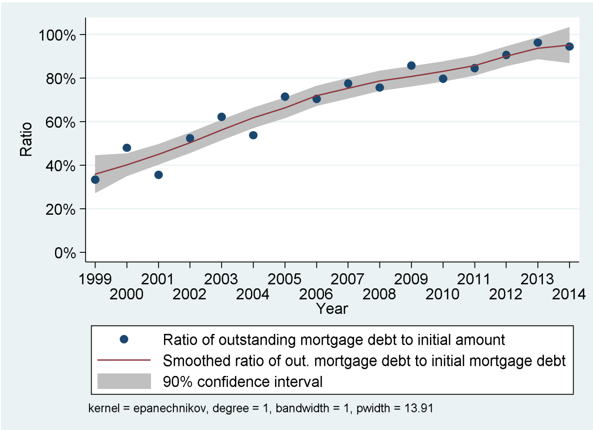




Source: Own calculations based on the LU-HFCS wave 1 and 2. Results are imputed and weighted.
Note: The smoothed line and confidence intervals are estimated using Kernel-weighted local polynomial smoothing (Stata manual 13, command lpoly).

Third, most households have repaid a significant part of the mortgage principal since the date of purchase. In the 2nd wave of the survey, the average household had repaid 24.5% of its initial mortgage. Households with mortgages originated in 2012 still had 90% of their initial amount to repay in 2014 (Figure 5). Households with mortgages originated in 2002 had only 50% to repay in 2014.

Figure 5: Ratio of outstanding mortgage debt to initial amount by year of origination



Source: Own calculations based on the LU-HFCS wave 2. Results are imputed and weighted.
Note: The smoothed line and confidence intervals are estimated using Kernel-weighted local polynomial smoothing (Stata manual 13, command lpoly). The year 1999 summarizes all years from 1983-1999.

In summary, the appreciation of real estate property and the partial repayment of mortgages through time contributed to a significant reduction in the current LTV ratios of the outstanding stock of mortgages. In 2014, the median LTV ratio of the outstanding stock of mortgages was only 34.6% (Giordana and Ziegelmeyer, 2017) while the median LTV at the time of loan origination was 78%.

3.3.5 Combined shock scenarios

In the rest of this section, we combine several individual shocks in a medium-stress scenario and a high-stress scenario (Table 1). We focus on the scenario implementations that introduce the shock to income via a rise in the unemployment rate (a uniform decline in household income produces similar results).

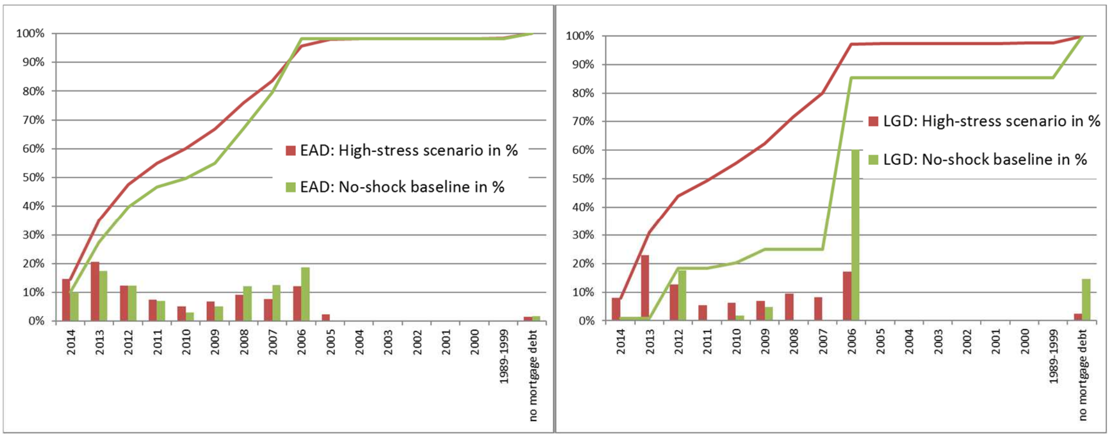
The outcome of the scenarios combining several shocks also appear in Table 5 above. Not surprisingly, the medium- and high-stress scenarios have more sizeable effects than the individual shocks considered separately. The medium-stress scenario increases the mean PD by 0.9 ppt compared to the no-shock baseline, resulting in an EAD ratio of 6.7% and a LGD ratio of 1.8%. In the high-stress scenario, the mean PD increases by 2.2 ppt, with the EAD ratio reaching 9.6% and the LGD ratio 4.2%. These results highlight how bank losses from the resident household sector are sensitive to adverse economic shocks.

In spite of differences in method, scenarios and reference periods, our results are similar to those for other EA countries. We find an EAD ratio of 6.7% for Luxembourg in the medium-stress scenario, while Ampudia et al. (2016) find 5.7% for their total sample, with country-specific results ranging from 4.6% in Germany to 16.5% in Greece. Our corresponding estimate of the LGD ratio for Luxembourg was 1.8%, the same as Ampudia et al. found in their total sample, with their country-specific results ranging from 0.7% in Belgium to 4.2% in Austria.[33]

3.3.5.1 Results by year of mortgage origination

To further analyse the outcome of the combined shock scenario, Figure 6 decomposes the total EAD and LGD by year of mortgage origination (for the household's most recent mortgage) and compares the no-shock baseline (in green) to the high-stress scenario (in red). The left panel reports the share of total EAD represented by each household group (using bars), as well as the cumulative distribution (using lines). The right panel analyses the LGD in a similar fashion. Households without mortgage debt (meaning those with only private, credit card, overdraft or consumer debt) appear at the far right in both panels.

Figure 6: Share of total EAD and LGD by year of mortgage origination



Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities). The year of mortgage origination refers to the most recent mortgage (whether on the household main residence or on other real estate property). The lines are the corresponding cumulative distributions.

[33] Meriküll and Rõõm (2017) combine shocks to mimic the Great Recession. Their results are not comparable to ours as they assume a fall in interest rates in response to the financial stress caused by increasing unemployment and declining real estate prices.

In the no-shock baseline, households without mortgage debt represent only 2% of total EAD but 15% of total LGD (green bars). The remaining EAD is concentrated in households that took out their mortgage in 2006 (19%) and in 2013 (17%), while the remaining LGD is mainly associated with households that took out their mortgage in 2006 (60%) and 2012 (18%).

In the high-stress scenario (red bars, Figure 6), EAD is concentrated among households that took out their mortgage in 2013 and in 2014, while LGD is concentrated in 2006 and 2013. About one third of households took out their mortgage before 2006 and they represent around 20% of outstanding debt (Figure 3) but account for less than 1% of the losses. This is consistent with the fact that these households have paid back a substantial part of their original loan (Figure 5) and suggests that their collateral may have appreciated in value. Households who have no mortgage debt represent only 2.5% of losses, reflecting the dominant share of mortgages in total household debt.

Comparing the no-shock baseline to the high-stress scenario, the pattern for EAD is similar (left panel). However, in the high-stress scenario the EAD is somewhat more concentrated among households with recent debt. In the right panel, the distribution of LGD by year of origination differs more sharply. This mainly reflects the fall in real estate prices in the high-stress scenario, which affects the value of available collateral.

3.3.5.2 Results by household characteristics

For each of the two stressed scenarios, Table 6 reports the mean PD, EAD ratio, LGD ratio and the share of LGD in EAD for groups of households with different characteristics. Within each group, the EAD and LGD ratios are calculated as the ratio of total EAD or LGD in the given group to total debt held by the given group. Table 14 in Appendix B reports similar results when the fall in household income is implemented as a uniform decline across households instead of a rise in unemployment that only affects selected households.

As in subsection 3.2, the PD, EAD ratio and LGD ratio differ strongly across groups with different household characteristics. The high-stress scenario generates substantial social costs. Socio-economically disadvantaged households (those with low net wealth, low income, low education, 3+ dependent children, or "other not working" employment status[34]) have PDs between 7.7% and 14.8%.

[34] This last category includes cases where the head of household is inactive, but excludes the retired. It includes student/pupil/unpaid intern; permanently disabled; fulfilling domestic tasks; other not working for pay.

Table 6: PD, EAD and LGD for different groups of indebted households – stress test results of combined shocks

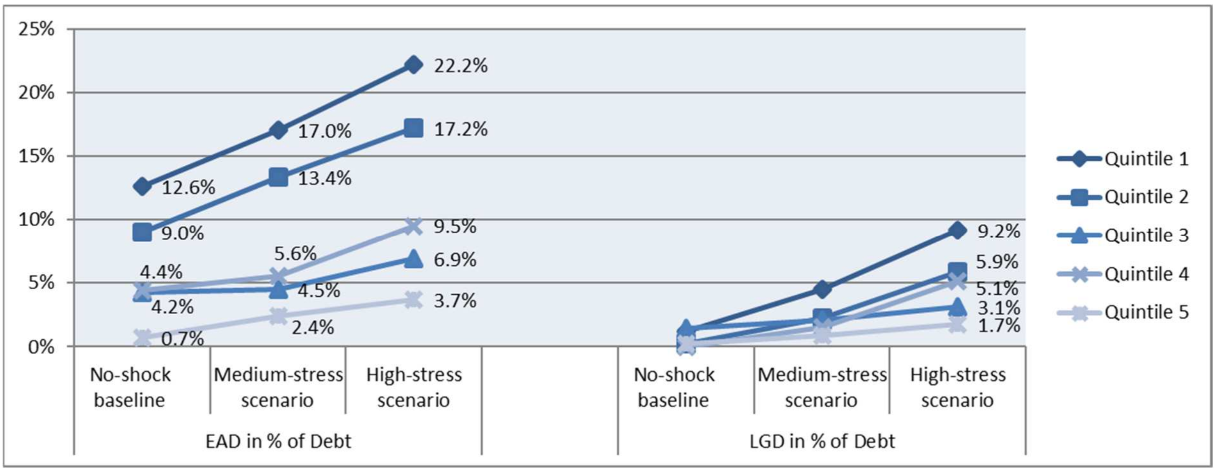
		Medium-stress scenario				High-stress scenario			
Variable name	Variable label	Mean PD	EAD in % of Debt	LGD in % of Debt	LGD/EAD in %	Mean PD	EAD in % of Debt	LGD in % of Debt	LGD/EAD in %
Total		4.0%	6.7%	1.8%	27.2%	5.3%	9.6%	4.2%	43.4%
Gender	Male	4.1%	8.1%	2.6%	32.0%	5.4%	10.6%	4.8%	45.2%
	Female	3.7%	4.7%	0.7%	14.8%	5.1%	8.1%	3.3%	40.1%
Age classes*	16-34	3.1%	3.4%	0.8%	22.6%	4.1%	5.2%	2.3%	43.8%
	35-44	4.0%	4.6%	1.8%	39.9%	6.5%	9.3%	4.9%	52.0%
	45-54	3.1%	8.1%	2.4%	29.2%	4.1%	10.1%	3.9%	38.4%
	55-64	6.8%	20.0%	3.4%	17.0%	7.2%	21.2%	7.9%	37.1%
	65+	2.7%	5.0%	1.6%	32.5%	4.3%	9.4%	3.1%	33.0%
Country of birth*	Luxembourg	3.6%	7.9%	2.2%	27.3%	5.0%	11.5%	5.0%	43.3%
	Portugal	6.3%	7.2%	2.8%	38.9%	8.6%	10.5%	5.2%	49.1%
	France	1.1%	0.7%	0.2%	24.3%	2.0%	2.4%	1.2%	48.3%
	Belgium	2.2%	0.5%	0.4%	78.0%	2.4%	0.7%	0.4%	59.8%
	Italy	6.7%	2.3%	0.5%	21.8%	7.5%	3.6%	0.6%	17.4%
	Germany	9.1%	23.8%	3.9%	16.3%	9.9%	25.9%	9.9%	38.2%
	Other countries	4.1%	0.5%	0.4%	72.8%	4.8%	1.6%	0.9%	54.2%
Household size	1 member	3.8%	9.0%	1.9%	20.8%	4.7%	11.3%	4.4%	39.3%
	2 members	2.9%	5.8%	1.7%	30.2%	4.1%	7.5%	3.1%	41.8%
	3 members	4.5%	2.4%	0.5%	21.8%	5.4%	4.2%	1.5%	34.9%
	4 members	2.7%	4.6%	1.7%	37.4%	4.6%	9.5%	5.3%	56.0%
	5+ members	8.0%	16.4%	4.2%	25.7%	9.8%	20.4%	8.1%	39.4%
Number of dependent children	no children	2.9%	6.5%	1.7%	25.8%	3.9%	8.4%	3.4%	40.3%
	1 child	4.7%	2.9%	0.4%	13.8%	6.0%	5.2%	1.8%	34.1%
	2 children	4.1%	6.1%	2.4%	38.9%	5.9%	10.9%	6.3%	57.4%
	3+ children	8.9%	18.2%	4.7%	25.5%	10.9%	22.6%	8.7%	38.7%
Marital status*	Single	3.9%	6.3%	1.2%	18.3%	5.2%	8.1%	3.3%	40.0%
	Couple	3.6%	6.1%	2.1%	33.5%	5.0%	9.5%	4.5%	47.3%
	Divorced	5.6%	10.7%	2.1%	19.7%	6.8%	13.5%	4.7%	34.6%
	Widowed	3.0%	3.1%	0.0%	0.0%	4.3%	4.4%	0.0%	0.0%
Education level*	Low (ISCED=0,1,2)	6.1%	10.7%	4.7%	44.2%	8.6%	17.7%	10.5%	59.2%
	Middle (ISCED=3,4)	4.5%	11.6%	2.1%	17.9%	5.8%	15.2%	5.1%	33.4%
	High (ISCED=5,6)	2.0%	2.0%	0.8%	38.6%	2.7%	3.2%	1.6%	51.9%
Employment status*	Employed	3.2%	4.4%	0.8%	18.6%	4.6%	7.3%	2.9%	40.0%
	Self-Employed	3.2%	10.2%	3.1%	30.6%	6.6%	15.2%	5.8%	38.0%
	Unemployed	7.6%	5.9%	1.7%	29.1%	7.9%	7.0%	3.0%	42.7%
	Retired	5.2%	16.8%	4.3%	25.4%	6.1%	18.7%	8.1%	43.1%
	Other not working	7.2%	20.2%	10.6%	52.6%	7.7%	21.6%	14.1%	65.5%
Housing status	Owner-outright	0.9%	1.6%	0.0%	0.0%	1.3%	2.6%	0.5%	18.7%
	Owner-with mortgage	3.7%	6.8%	1.9%	28.1%	5.6%	10.2%	4.4%	43.5%
	Renter or other	7.0%	10.4%	2.7%	26.1%	7.8%	11.4%	5.4%	47.3%
Total gross income	Quintile 1	11.9%	17.0%	4.5%	26.3%	14.8%	22.2%	9.2%	41.3%
	Quintile 2	4.1%	13.4%	2.2%	16.6%	5.3%	17.2%	5.9%	34.3%
	Quintile 3	1.6%	4.5%	2.1%	45.6%	2.5%	6.9%	3.1%	45.0%
	Quintile 4	1.8%	5.6%	1.5%	27.7%	2.8%	9.5%	5.1%	53.9%
	Quintile 5	0.4%	2.4%	0.9%	36.4%	0.9%	3.7%	1.7%	47.1%
Total net wealth	Quintile 1	9.6%	11.1%	6.4%	57.5%	11.5%	19.0%	13.5%	71.1%
	Quintile 2	5.0%	8.6%	2.6%	29.9%	7.4%	11.6%	5.5%	47.9%
	Quintile 3	1.4%	1.5%	0.3%	18.3%	2.1%	2.1%	0.6%	27.5%
	Quintile 4	2.6%	11.0%	1.7%	15.5%	3.2%	12.3%	4.4%	35.7%
	Quintile 5	1.1%	3.6%	0.1%	2.1%	2.2%	6.7%	0.7%	10.2%

Source: Own calculations based on the 2^{nd} wave of the LU-HFCS. Data are multiply imputed and weighted. We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities). Personal characteristics indicated by an asterisk refer to the "financially knowledgeable person" (FKP). The table focuses on stress scenarios that implement the income shock as an increase in the unemployment rate. Table 14 in Appendix A reports similar results from a uniform decline in household income.

The LGD ratio in these groups ranges between 8.7% and 14.1%, and the part of EAD not covered by collateral ranges between 38.7% and 71.1% (last column of Table 6). Overall, socio-economically disadvantaged households have a limited impact on potential bank losses from lending to the household sector. For instance, in the high-stress scenario households with three or more dependent children have a substantially higher average PD (10.9%), EAD ratio (22.6%) and LGD ratio (8.7%). However, this group accounts for only 9.7% of total debt (Table 4). As a result, this group contributes only around 0.8 ppt (=8.7%*9.7%) to the total LGD ratio of 4.2%. A similar argument applies to other disadvantaged household groups, such as those with low wealth, income or education.

Comparing income quintiles (Figure 7), the EAD and LGD ratios decrease almost monotonically as income increases. In the no-shock baseline, the EAD (LGD) ratio falls from 12.6% (1.2%) in the first income quintile to 0.7% (0.2%) in the fifth one. Likewise, in the high stress scenario, the EAD (LGD) ratio falls from 22.2% (9.2%) in the first income quintile to 3.7% (1.7%) in the fifth one.

Figure 7: EAD and LGD ratios by income quintile

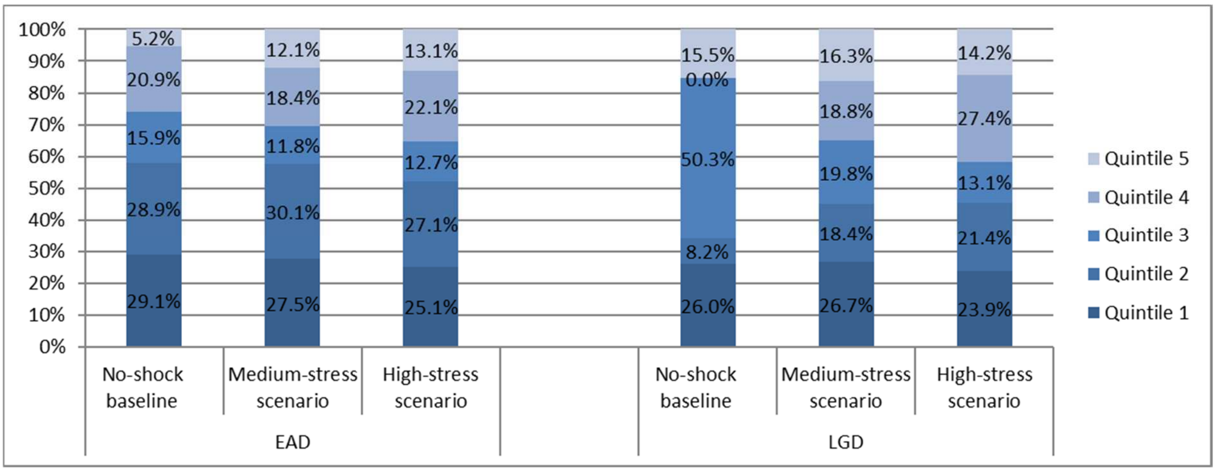


Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted. We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities).

Figure 8 focuses on the share of overall EAD and LGD that is attributable to households from each income quintile. In the no-shock baseline, households in the first two income quintiles represent 58% of total EAD. In the high-stress scenario, this share declines to 52%, but it remains disproportionately high. However, in terms of total LGD the first two income quintiles represent only 34% in the no-shock baseline and 45% in the high stress scenario. These figures are closer to the 40% share of the total population represented by households in the first two quintiles of the income distribution. Discrepancies between the shares in LGD and the shares in EAD reflect differences in the distributions of real estate collateral across income quintiles. This is also a function of the changing composition of debt across income quintiles. For example, mean non-mortgage debt represents 17% of mean mortgage debt in the lowest income quintile, while this ratio is only 11% in quintiles two, three and four and drops to 6% in the top one. By reducing the value of collateral, the fall in real estate prices increases the share of total LGD represented by households in quintiles 4 and 5. Since many low-income households have no collateral anyway, their share of total LGD declines with the fall in real estate prices.

Households in the third income quintile provide an extreme illustration of the impact of the distribution of collateral, as they represent 50% of total LGD in the no-shock baseline but only 13% in the high stress scenario. In the no-shock baseline, these households represent a relatively small share of total EAD (15.9%), but a substantial share of total LGD (50%), suggesting that their low collateral values are key. In the stress scenarios, households in the third income quintile represent only 20% (medium stress) or 13% (high stress) of total LGD. This reduction is driven by two factors. First, the increase in PDs in the stress scenarios is offset by the spare collateral held by households in this group. Second, the fall in real estate prices increases bank losses from other income quintiles with less spare collateral. This is particularly striking for the fourth quintile, where the share of LGD increases from practically zero in the no-shock baseline to more than 27% in the high stress scenario. Naturally, this increase reduces the relative share of the third quintile.

Figure 8: Contributions of income quintiles to EAD and LGD



Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted. We use the FM 1 definition of financial margin (household-specific expenditure on food & utilities).

4 Discussion

Our stress test results suggest that bank losses from exposures to resident households are quite sensitive to adverse economic conditions, but remain moderate compared to the level of bank capitalisation in Luxembourg[35,36]. However, our adverse scenarios do not consider bank losses on exposures to other institutional sectors. The scenarios include increases in interest rates and falls in income and asset prices that would normally affect other borrowers, including non-resident households as well as non-financial corporations (both in Luxembourg and abroad). If one were to also consider bank losses from these other exposures (and the potential impact on interbank loans), our adverse scenarios could potentially generate systemic effects.

The structure of the Luxembourg banking sector is also relevant to evaluate the consequences of potential bank losses from the household sector[37]. As mentioned in the introduction, the BCL Financial Stability Review regularly observes that loans to the household sector (including to non-residents) are concentrated in a limited number of banks. Calculating the share of the household sector in the loan portfolio of each bank, the distribution of this share across banks is associated with a Gini index of 0.91, close to the maximum value of one that represents the highest level of concentration[38]. Considering only loans to resident households, concentration is even higher, with the Gini index reaching 0.97.

In fact, bank-level data reveals several important observations: (i) half of Luxembourg banks provide no loans to households, (ii) nine banks out of ten allocate less than one third of their loan portfolio to households, and (iii) only one bank in twenty devotes more than half of its loan portfolio to households.

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35 Available data do not permit the exact allocation of the simulated losses to individual banks. However, under the assumption that each of the ten banks with the highest exposure to resident households suffered the full-fledged loss given default in the high stress scenario (4.18% in Table 5), their capitalisation would be sufficient. In 2014, loss given default in the high stress scenario represented between 0.3 and 47 percent of these banks' Common Equity Tier 1 capital (CET1) and their CET1 ratios remained above the minimum required after the shock.

36 Jin and Nadal De Simone (2017) also find limited systemic risk from household loans. Their study uses individual data for six other systemically important institutions and 17 investment banks for the period 2008q4-2015q2. They construct the household sector balance sheet using aggregate data from the financial accounts and other sources.

37 These paragraphs refers to bank-level data for 2014, when the second wave of HFCS was collected. Since banking sector structure tends to be relatively stable, more recent data would lead to similar conclusions.

38 The Gini index is calculated using the SGINI routine developed by Van Kerm (2009).

Individual bank data also suggests that loans to households are concentrated in relatively large banks, which are often systemically important financial institutions[39]. In 2014, the ten banks with the highest share of household loans in the banking sector represented more than 32% of aggregate loans (all sectors), 79% of loans to households, 94% of loans to resident households and 95% of mortgage loans to resident households in the banking sector. In 2017, the Luxembourg macro-prudential authority designated five of these banks as Other Systemically Important Institutions[40].

The low LGD ratio in our simulations may reflect lower LTV ratios at loan origination[41]. Table 7 reports average LGD ratios for households in each quintile of the distribution of the LTV ratio at origination. As expected, simulated bank losses were generally lower for households with lower LTV ratios, since these correspond to higher collateral. For instance, in the high-stress scenario, banks would lose 25 million euros from households whose LTV ratio was in the lowest quintile (1% of the debt held by these households), but they would lose 312 million euros from households whose LTV ratio was in the highest quintile (9% of their debt). However, one may observe in the table that both total LGD and the LGD ratio are actually lower in the second quintile of the LTV ratio distribution than in the first quintile. Since households in the second quintile had higher LTV ratios at origination, they have had less collateral relative to their mortgage debt at origination, which would lead one to expect a higher LGD. The observation that LGD is actually lower among households in the second quintile can be attributed to different factors: (1) they may have repaid more of their outstanding debt; (2) their real estate collateral may have appreciated more; (3) they may have lower PDs, either because they have higher financial margins or because they have higher levels of liquid assets or liquid assets of a type that is less sensitive to the simulated shocks.

[39] Drehmann and Tarashev (2011) and Moore and Zhou (2013) find that bank size is highly correlated with the degree of systemic importance.

[40] See *Avis et Recommandation du Comité du Risque Systémique* of the 9th of October 2017 (CRS/2017/005).

[41] Other mitigating factors include low DSI ratios and high household levels of liquid assets.

Table 7: LGD by LTV ratio at loan origination

LTV at loan origination	Debt (million euros)	High-stress scenario Total LGD (million euros)	High-stress scenario LGD ratio (% of debt)	No-shock baseline Total LGD (million euros)	No-shock baseline LGD ratio (% of debt)
No HMR mortgage	4091	130.3	3.2%	17.4	0.4%
Quintile 1	2429	25.5	1.0%	0	0%
Quintile 2	2738	6.8	0.2%	0	0%
Quintile 3	3228	108.6	3.4%	17.8	0.6%
Quintile 4	4595	274.4	6.0%	2.0	0.0%
Quintile 5	3449	312.4	9.1%	67.3	2.0%
Total	20530	857.9	4.2%	104.5	0.5%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.
Note: Debt includes both mortgage and non-mortgage debt.

However, the impact of borrower-based policies on the composition of household balance sheets may have unintended consequences. For instance and for purely illustrative purposes, a cap on the LTV ratio will limit how much households can borrow, forcing some to sell their liquid assets to provide more finance for house purchase. These households will then be unable to smooth economic shocks by selling their liquid assets, making them more vulnerable. If these households default, their assets will be more concentrated in real estate, so bank losses may turn out to be even more sensitive to real estate prices. Combining several different borrower-based instruments could mitigate this outcome by requiring indebted households to have a sufficient financial margin to save and build a diversified portfolio of assets.

5 Conclusion

This paper evaluates potential bank losses from household defaults under severe economic conditions. We conduct a household stress test on data from a representative survey using methods applied at the International Monetary Fund, European Central Bank and other national central banks. First, we calculate the probability of default (PD) at the level of individual households, using a measure of the financial margin that combines survey data on household income, expenses and liquid assets. We then calculate aggregate bank exposure at default (EAD) by multiplying outstanding loans by individual probabilities of default and summing across households. Finally, we obtain aggregate bank loss given default (LGD) on household loans by assuming that banks recover real estate assets from defaulting households and liquidate them with a haircut. To simulate adverse economic conditions, we repeat the exercise using scenarios that combine shocks to real estate prices, liquid assets, household income and interest rates.

In the no-shock baseline, we calculate a 3.1% average PD across indebted households. In the absence of shocks, bank EAD represents 4.7% of all bank loans to households. After imposing a haircut on the real estate assets of defaulting households, bank LGD in the no-shock baseline represents only 0.51% of bank exposure to resident households. The stress test consists in repeating this exercise under different shocks while assuming that the real estate market remains liquid. The 50% fall in real estate prices has the largest impact, raising the LGD ratio to 2.21%. The shock to interest rates, which go up by 4 percentage points, raises the LGD ratio to 0.89%. Considered individually, the other shocks have only marginal impacts on the LGD ratio. When several individual shocks are combined in a high-stress scenario, bank EAD rises to 9.6% of total bank exposure to the household sector and bank LGD reaches 4.2%. This level of losses may still seem limited compared to the current level of bank capitalisation in Luxembourg, but the high-stress scenario would presumably trigger additional losses from loans to non-financial corporations (not considered here), both in Luxembourg and abroad, and from non-resident households. In addition, mortgage lending in Luxembourg is concentrated in a limited number of important banks, so the high-stress scenario could also generate losses on interbank loans and systemic effects that are beyond the scope of this household stress test.

The high-stress scenario also generates substantial social costs, as defaults are relatively high among socio-economically disadvantaged households. In particular, households with low net wealth, low income, low education, three or more dependent children, or a head of household with “other not working” employment status, have PDs between 7.7% and 14.8%, leading to LGD ratios ranging from 8.7% to 14.1%.

To our knowledge, this is the first study to implement a household stress test using micro data for Luxembourg. Although our methods, scenarios, data and reference period may differ from other studies in the literature, our results are similar to those for other EA countries (Ampudia et al., 2016; Meriküll and Rõõm, 2017).

Our main conclusion is that bank losses from exposures to the household sector appear to be quite sensitive to financial stress, despite allowing for three mitigating factors. First, households in Luxembourg hold substantial liquid assets, which allow them to cover expenses for several months even under stressed conditions. Second, many households have repaid a significant part of their mortgages, progressively reducing their leverage since the loans were originated. Third, reported loan-to-value ratios at mortgage origination appear not to be excessive, limiting losses in case of default.

The literature on household stress tests adopts a static approach that does not account for feedback effects between households, banks and other economic agents. One exception is the micro-macro model by Gross and Población García (2016). Such a dynamic version of household stress tests remains a project for future research.

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7 Appendix

Appendix A: Literature overview

Table 8: Previous papers on household stress tests using micro data

	Scope		Data			Method		
Authors (year of publication)	Households	Banks	Source	Year	Country	Identification of vulnerable hhs	PD	Link with banking sector
Albacete and Fessler (2010)	x	x	EU-SILC, Austrian Consumption Survey, HSHW, SFHW	2008	AT	Financial margin-based approach	Binary default interpretation	EAD and LGD ratios (**no calibration**)
Albacete and Lindner (2013)	x	x	HFCS	2010	AT	Indicator-based approach	Binary default interpretation	EAD and LGD ratios (**no calibration**)
Albacete et al. (2014)	x	x	HFCS	2010	AT	Financial margin-based approach	Binary default interpretation	EAD (called share of exposure to vulnerable households, ShvH) and LGD (**no calibration**)
Ampudia et al. (2016)	x	x	HFCS	2010	AT, BE, CY, FR, DE, GR, IT, PT, SK, ES	Financial margin-based approach	Continuous default interpretation	**Calibration** of PD aimed at fitting EAD ratio with the observed NPL (to households) ratio in the banking sector
Bilston et al. (2015)	x	x	HILDA	2002, 2006, 2010	AU	Financial margin-based approach	Binary default interpretation	EAD (called weighted average probability of default, WPD) and LGD (called weighted average debt at risk, DAR) (**no calibration**)
Bricker et al. (2012)	x	-	SCF	2007, 2010	US	Indicator-based approach	-	-
Del-Rio and Young (2005)	x	-	BHPS	1995, 2000	GB	Indicator & FM-based approaches	Continuous default interpretation	-
Djoudad (2012)	x	-	Canadian Financial Monitor survey	2008	CA	Indicator-based approach	Binary default interpretation	-
ECB (2013)	x	-	HFCS	2010	Euro area	Indicator-based approach	-	-
Faruqui et al. (2012)	x	-	Canadian Financial Monitor survey	2012	CA	Indicator-based approach	Binary default interpretation	-
Galuščák et al. (2016)	x	-	HBS	2010, 2011, 2012	CZ	Financial margin-based approach	Binary default interpretation	-
Giordana and Ziegelmeyer (2017)	x	-	HFCS	2010, 2014	LU	Indicator-based approach	Binary default interpretation	-
Gross and Población García (2016)	x	x	HFCS	2010	Euro area	Similar to the FM-based approach	Continuous default interpretation	EL (expected loss), EAD, LGD, RWA, interest income
Herrala and Kauko (2007)	x	-	Annual survey/registers data by Statistics Finland	2000-2004	FI	Indicator & FM-based approaches	Binary default interpretation	-
Hlavác et al. (2012)	x	-	HBS, SILC	2011	CZ	Financial margin-based approach	Binary default interpretation	-
Holló and Papp (2007)	x	x	Survey by MNB	2007	HU	Financial margin-based approach	Binary default interpretation	EAD (called debt-at-risk), LGD (**no calibration**)
IMF (2011)	x	x	NMG consulting survey	2010	UK	Indicator-based approach	Binary default interpretation	EAD (called debt-at-risk), LGD (**no calibration**)
IMF (2012)	x	x	EFF	2008	ES	Indicator-based approach	Binary default interpretation	EAD (called exposure), LGD (called debt held by vulnerable households not covered by assets) (**no calibration**)
IMF (2017)	x	-	HFCS	2009	FI	Financial margin-based approach	Binary default interpretation	-
Johansson and Persson (2006)	x	x	HEK survey	2004	SE	Financial margin-based approach	Binary default interpretation	EAD and LGD ratios (**no calibration**)
Karasulu (2008)	x	-	KLIPS	2006	KR	Indicator & FM-based approaches	Binary default interpretation	-
Martinez et al. (2013)	x	x	SHF	2007	CL	Indicator-based approach	Continuous default interpretation	EAD (called debt-at-risk), (**no calibration**)
Meriküll and Rõõm (2017)	x	x	HFCS	2013	EE	Financial margin-based approach	Continuous default interpretation	**Calibration** of PD aimed at fitting EAD ratio with the observed NPL (to households) ratio in the banking sector
Michelangeli and Pietrunti (2014)	x	-	SHIW	2002-2012	IT	Indicator-based approach	-	-
Riksbank (2009)	x	x	HEK survey	2008	SE	Financial margin-based approach	Binary default interpretation	EAD (**no calibration**)
Sugawara and Zalduendo (2011)	x	x	HBS	2008	HR	Financial margin-based approach	Binary default interpretation	EAD (**no calibration**)

Appendix B: Robustness tables for stress tests on all indebted household

Table 9: Summary statistics on liquid assets and share of households with insufficient liquid assets to cover negative financial margin (FM) for the indicated number of months

	Liquid assets (LIQ)		Share of households with insufficient liquid assets to cover negative FM for the indicated number of months					
	Mean	Median	No liquid assets	1	2	3	6	12
All indebted households using the following FM definition								
FM 1: Food & utilities (individual)	100,302 €	15,760 €	0.5%	2.7%	3.6%	4.2%	5.4%	6.2%
FM 2: Food & utilities (median)	100,302 €	15,760 €	0.4%	2.5%	3.3%	3.9%	5.0%	6.0%
FM 3: Net income (median in quintile 1)	100,302 €	15,760 €	0.4%	2.4%	3.2%	3.9%	5.0%	5.9%
FM 4: Consumption of goods & services (60% of median)	100,302 €	15,760 €	0.4%	2.4%	3.2%	3.9%	5.0%	6.0%
Indebted households with neg. FM using the following FM definition								
FM 1: Food & utilities (individual)	51,055 €	4,380 €	4.9%	25.1%	33.2%	38.7%	49.4%	56.2%
FM 2: Food & utilities (median)	40,893 €	3,060 €	3.7%	21.4%	28.0%	33.8%	43.0%	51.9%
FM 3: Net income (median in quintile 1)	43,325 €	2,960 €	3.9%	21.9%	28.9%	35.2%	44.7%	53.6%
FM 4: Consumption of goods & services (60% of median)	43,322 €	2,976 €	3.9%	22.0%	28.8%	35.1%	44.6%	53.6%
	Liquid assets (LIQ)				**Average PD**			
	Mean	**Median**	**No liquid assets**	**1**	**2**	**3**	**6**	**12**
All indebted households using the following FM definition								
FM 1: Food & utilities (individual)	100,302 €	15,760 €	0.5%	2.1%	2.7%	3.1%	4.0%	4.9%
FM 2: Food & utilities (median)	100,302 €	15,760 €	0.4%	1.9%	2.5%	3.0%	4.0%	5.1%
FM 3: Net income (median in quintile 1)	100,302 €	15,760 €	0.4%	1.8%	2.3%	2.8%	3.7%	4.9%
FM 4: Consumption of goods & services (60% of median)	100,302 €	15,760 €	0.4%	1.8%	2.3%	2.8%	3.8%	4.9%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

Table 10 : PD, EAD and LGD for different groups of indebted households (no-shock baseline)

Variable name	Variable label	Mean PD in %				EAD in % of Debt				LGD in % of Debt			
		FM 1	FM 2	FM 3	FM 4	FM 1	FM 2	FM 3	FM 4	FM 1	FM 2	FM 3	FM 4
Total	Total	3.1	3.0	2.8	2.8	4.7	4.4	4.3	4.3	0.51	0.47	0.46	0.46
Gender	Male	3.2	3.1	2.7	2.7	5.8	5.4	5.3	5.3	0.75	0.66	0.65	0.65
	Female	2.8	2.9	2.8	2.8	3.2	2.8	2.7	2.7	0.15	0.19	0.19	0.19
Age classes*	16-34	2.1	3.2	2.4	2.5	2.1	2.0	1.9	1.9	0.08	0.12	0.10	0.10
	35-44	3.1	2.7	2.5	2.5	2.4	1.9	1.7	1.8	0.54	0.41	0.40	0.40
	45-54	2.2	2.1	2.1	2.1	5.5	4.8	4.7	4.7	1.12	1.18	1.17	1.17
	55-64	6.3	5.1	5.1	5.1	18.3	18.4	18.3	18.3	0.17	0.07	0.07	0.07
	65+	1.4	1.7	1.6	1.6	3.5	3.8	3.7	3.7	0.38	0.40	0.39	0.39
Country of birth*	Luxembourg	2.6	2.8	2.4	2.5	5.4	5.2	5.1	5.1	0.61	0.63	0.61	0.62
	Portugal	4.6	4.1	4.0	4.0	4.6	2.3	2.1	2.1	0.86	0.42	0.38	0.39
	France	0.5	1.0	0.8	0.9	0.3	0.4	0.3	0.3	0.00	0.00	0.00	0.00
	Belgium	1.9	1.9	1.9	1.9	0.3	0.3	0.3	0.3	0.32	0.32	0.31	0.31
	Italy	5.8	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.49	0.00	0.00	0.00
	Germany	8.1	8.3	8.2	8.2	20.8	21.4	21.2	21.2	0.00	0.00	0.00	0.00
	Other countries	3.8	4.0	4.0	4.0	0.3	0.4	0.4	0.4	0.28	0.42	0.41	0.42
Household size	1 member	2.7	4.0	3.1	3.2	6.7	7.0	6.9	6.9	0.08	0.18	0.15	0.15
	2 members	2.6	2.5	2.4	2.5	5.3	5.2	5.1	5.1	1.05	1.05	1.05	1.05
	3 members	3.5	3.1	3.0	3.0	1.3	1.4	1.3	1.3	0.21	0.19	0.18	0.18
	4 members	1.8	1.4	1.4	1.4	2.4	2.4	2.3	2.3	0.44	0.41	0.40	0.40
	5+ members	6.2	4.8	4.7	4.7	10.7	7.7	7.4	7.4	0.67	0.34	0.31	0.32
Number of dependent children	no children	2.2	2.8	2.4	2.4	5.2	5.4	5.3	5.3	0.61	0.65	0.63	0.64
	1 child	3.8	3.4	3.3	3.3	1.7	1.5	1.5	1.5	0.15	0.12	0.12	0.12
	2 children	3.0	2.4	2.3	2.3	3.6	3.6	3.5	3.5	0.55	0.53	0.52	0.52
	3+ children	7.0	5.1	5.1	5.1	11.9	8.0	7.7	7.8	0.79	0.37	0.34	0.35
Marital status*	Single	3.0	3.5	2.7	2.7	5.2	5.2	5.0	5.1	0.08	0.08	0.05	0.06
	Couple	2.9	2.5	2.4	2.4	4.0	3.3	3.3	3.3	0.73	0.65	0.64	0.65
	Divorced	4.5	4.7	4.5	4.5	7.8	8.1	7.9	7.9	0.29	0.41	0.40	0.40
	Widowed	1.0	1.6	1.3	1.4	1.0	1.6	1.4	1.4	0.00	0.00	0.00	0.00
Education level*	Low (ISCED=0,1,2)	4.3	4.5	4.2	4.3	8.0	6.7	6.5	6.5	2.28	2.00	1.96	1.97
	Middle (ISCED=3,4)	3.8	3.4	3.0	3.0	8.3	7.8	7.7	7.7	0.16	0.14	0.13	0.13
	High (ISCED=5,6)	1.5	1.7	1.6	1.6	1.1	1.2	1.1	1.1	0.23	0.26	0.26	0.26
Employment status*	Employed	2.4	2.5	2.4	2.4	2.8	2.7	2.6	2.6	0.11	0.13	0.13	0.13
	Self-Employed	1.7	1.6	1.6	1.6	4.4	4.2	4.1	4.1	0.78	0.78	0.78	0.78
	Unemployed	7.2	6.2	6.1	6.1	4.4	5.3	5.2	5.2	0.66	0.63	0.63	0.63
	Retired	4.4	3.1	3.0	3.0	16.0	15.9	15.9	15.9	0.30	0.15	0.15	0.15
	Other	6.2	7.4	5.1	5.3	17.4	13.3	12.9	13.0	5.99	5.28	5.13	5.15
Housing status	Owner-outright	0.4	0.5	0.4	0.4	0.6	0.7	0.6	0.6	0.00	0.00	0.00	0.00
	Owner-with mortgage	2.6	2.4	2.3	2.3	4.6	4.1	4.0	4.1	0.53	0.48	0.47	0.47
	Renter or other	6.1	6.4	5.5	5.6	8.8	9.3	9.1	9.1	0.77	0.83	0.76	0.77
Total gross income	Quintile 1	9.3	9.4	8.3	8.4	12.6	11.4	11.1	11.2	1.22	1.13	1.05	1.06
	Quintile 2	3.1	2.9	2.7	2.7	9.0	7.6	7.3	7.4	0.28	0.16	0.15	0.15
	Quintile 3	1.5	1.2	1.2	1.2	4.2	4.2	4.2	4.2	1.45	1.41	1.40	1.40
	Quintile 4	1.4	1.4	1.4	1.4	4.4	4.5	4.4	4.4	0.00	0.00	0.00	0.00
	Quintile 5	0.1	0.1	0.1	0.1	0.7	0.7	0.7	0.7	0.23	0.23	0.23	0.23
Total net wealth	Quintile 1	8.2	8.3	7.3	7.4	8.0	8.2	8.0	8.1	3.28	3.34	3.27	3.28
	Quintile 2	4.2	4.0	3.8	3.8	7.1	6.2	6.0	6.0	0.34	0.17	0.16	0.16
	Quintile 3	0.6	0.5	0.4	0.4	0.5	0.4	0.4	0.4	0.02	0.02	0.02	0.02
	Quintile 4	1.9	2.0	1.9	1.9	8.5	8.7	8.6	8.6	0.00	0.00	0.00	0.00
	Quintile 5	0.5	0.3	0.3	0.3	1.2	0.5	0.5	0.5	0.00	0.00	0.00	0.00

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

Note: Financial margin (FM) 1: Food & utilities (individual); FM 2: Food & utilities (median); FM 3: Disposable income (median in quintile 1); FM 4: Consumption of goods & services (60% of median). The quintiles for total gross income and total net wealth are adjusted to indebted households. Personal characteristics refer to the "financially knowledgeable person" (FKP) indicated by an asterisk.

Table 11: PD, EAD and LGD for all indebted households (Stress test using FM 2: Food & utilities (median))

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	LGD/EAD in %
	No-shock baseline		3.0%	4.4%	0.47%	10.9%
Individual shocks	Income	-5%	3.3%	4.6%	0.49%	10.8%
		-10%	3.6%	4.8%	0.53%	11.0%
		-20%	4.4%	5.6%	0.64%	11.3%
	Unemployment	+2 ppt	3.9%	4.5%	0.50%	11.0%
		+4 ppt	4.0%	4.6%	0.51%	11.1%
		+6 ppt	4.0%	4.7%	0.52%	11.1%
	Interest rate	+1 ppt	3.1%	4.8%	0.50%	10.4%
		+2 ppt	3.3%	5.6%	0.61%	10.8%
		+3 ppt	3.5%	6.2%	0.74%	12.0%
		+4 ppt	3.6%	6.7%	0.88%	13.1%
	Liquid assets (stocks and bonds; less liquid assets)	-10%; -20%	3.0%	4.4%	0.47%	10.8%
		-20%; -40%	3.0%	4.4%	0.47%	10.8%
		-30%; -60%	3.0%	4.4%	0.47%	10.8%
		-40%; -80%	3.0%	4.4%	0.47%	10.8%
		-50%; -100%	3.0%	4.4%	0.47%	10.8%
	Real estate	-10%	3.0%	4.4%	0.66%	15.0%
		-20%	3.0%	4.4%	0.93%	21.2%
		-30%	3.0%	4.4%	1.29%	29.4%
		-40%	3.0%	4.4%	1.66%	37.9%
		-50%	3.0%	4.4%	2.09%	47.8%
	Combined shock using income shock	medium	4.0%	6.4%	1.84%	28.7%
		high	5.6%	8.9%	3.93%	44.4%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

Table 12: PD, EAD and LGD for all indebted households (Stress test using FM 3: Disposable income (median in quintile 1))

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	LGD/EAD in %
	No-shock baseline		2.8%	4.3%	0.46%	10.8%
Individual shocks	Income	-5%	3.1%	4.5%	0.48%	10.6%
		-10%	3.3%	4.7%	0.50%	10.7%
		-20%	4.2%	5.3%	0.58%	10.9%
	Unemployment	+2 ppt	3.4%	4.4%	0.49%	11.0%
		+4 ppt	3.5%	4.5%	0.50%	11.0%
		+6 ppt	3.5%	4.6%	0.51%	11.1%
	Interest rate	+1 ppt	2.8%	4.7%	0.49%	10.4%
		+2 ppt	3.0%	5.4%	0.59%	11.0%
		+3 ppt	3.2%	6.0%	0.71%	11.8%
		+4 ppt	3.3%	6.6%	0.86%	13.2%
	Liquid assets (stocks and bonds; less liquid assets)	-10%; -20%	2.8%	4.3%	0.46%	10.8%
		-20%; - 40%	2.8%	4.3%	0.46%	10.8%
		-30%; -60%	2.8%	4.3%	0.46%	10.8%
		-40%; -80%	2.8%	4.3%	0.46%	10.8%
		-50%; -100%	2.8%	4.3%	0.46%	10.8%
	Real estate	-10%	2.8%	4.3%	0.64%	15.0%
		-20%	2.8%	4.3%	0.91%	21.2%
		-30%	2.8%	4.3%	1.26%	29.5%
		-40%	2.8%	4.3%	1.62%	37.9%
		-50%	2.8%	4.3%	2.05%	47.9%
	Combined shock using income shock	medium	3.7%	6.2%	1.78%	28.6%
		high	5.4%	8.7%	3.86%	44.4%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

Table 13: PD, EAD and LGD for all indebted households (Stress test using FM 4: Consumption of goods & services (60% of median))

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	LGD/EAD in %
	No-shock baseline		2.8%	4.3%	0.46%	10.8%
Individual shocks	Income	-5%	3.1%	4.5%	0.48%	10.7%
		-10%	3.3%	4.7%	0.51%	10.8%
		-20%	4.2%	5.4%	0.59%	10.9%
	Unemployment	+2 ppt	3.5%	4.4%	0.49%	11.0%
		+4 ppt	3.5%	4.5%	0.50%	11.1%
		+6 ppt	3.6%	4.6%	0.51%	11.1%
	Interest rate	+1 ppt	2.9%	4.7%	0.49%	10.4%
		+2 ppt	3.1%	5.5%	0.60%	10.8%
		+3 ppt	3.2%	6.1%	0.72%	11.9%
		+4 ppt	3.4%	6.6%	0.87%	13.1%
	Liquid assets (stocks and bonds; less liquid assets)	-10%; -20%	2.8%	4.3%	0.46%	10.8%
		-20%; - 40%	2.8%	4.3%	0.46%	10.8%
		-30%; -60%	2.8%	4.3%	0.46%	10.8%
		-40%; -80%	2.8%	4.3%	0.46%	10.8%
		-50%; -100%	2.8%	4.3%	0.47%	10.8%
	Real estate	-10%	2.8%	4.3%	0.64%	15.0%
		-20%	2.8%	4.3%	0.91%	21.2%
		-30%	2.8%	4.3%	1.27%	29.5%
		-40%	2.8%	4.3%	1.63%	37.9%
		-50%	2.8%	4.3%	2.05%	47.8%
	Combined shock using income shock	medium	3.8%	6.3%	1.79%	28.6%
		high	5.4%	8.7%	3.87%	44.4%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted.

Table 14 : PD, EAD and LGD for different groups of indebted households – combined shocks (uniform income decline)

		Medium-stress scenario				High-stress scenario			
Variable name	Variable label	Mean PD	EAD in % of Debt	LGD in % of Debt	LGD/EAD in %	Mean PD	EAD in % of Debt	LGD in % of Debt	LGD/EAD in %
Total		3.7%	6.4%	1.9%	29.1%	5.3%	9.3%	4.0%	43.4%
Gender	Male	3.8%	7.6%	2.6%	33.8%	5.5%	10.1%	4.5%	44.2%
	Female	3.4%	4.6%	0.8%	17.2%	4.9%	8.2%	3.4%	41.9%
Age classes*	16-34	2.7%	2.9%	0.7%	22.3%	5.7%	6.9%	2.7%	39.2%
	35-44	4.0%	4.9%	2.1%	43.2%	6.0%	8.7%	4.5%	51.3%
	45-54	2.9%	7.6%	2.4%	31.2%	4.3%	9.3%	3.8%	41.4%
	55-64	6.3%	18.8%	3.2%	17.2%	6.4%	19.3%	7.2%	37.4%
	65+	1.5%	3.9%	1.4%	35.2%	1.7%	4.8%	2.2%	46.2%
Country of birth*	Luxembourg	3.1%	7.6%	2.3%	29.7%	4.9%	10.8%	4.6%	42.3%
	Portugal	6.0%	7.1%	2.7%	38.1%	7.9%	10.7%	5.5%	51.3%
	France	1.4%	0.9%	0.1%	14.0%	2.8%	2.9%	1.3%	46.0%
	Belgium	2.0%	0.3%	0.3%	100.0%	2.1%	0.3%	0.3%	100.0%
	Italy	6.1%	1.2%	0.5%	42.6%	7.2%	2.4%	0.5%	20.3%
	Germany	8.3%	21.4%	3.5%	16.2%	8.5%	22.0%	8.4%	38.0%
	Other countries	4.2%	0.4%	0.4%	100.0%	5.9%	4.5%	2.3%	52.4%
Household size	1 member	3.1%	7.9%	1.8%	22.2%	5.6%	12.4%	4.2%	33.8%
	2 members	2.8%	5.5%	1.7%	30.4%	3.9%	6.9%	3.2%	46.6%
	3 members	4.2%	2.2%	0.5%	22.1%	4.9%	2.9%	1.1%	38.1%
	4 members	2.5%	5.1%	2.2%	42.8%	4.7%	9.5%	5.4%	57.1%
	5+ members	7.8%	15.5%	4.0%	26.0%	9.3%	19.7%	7.6%	38.4%
Number of dependent children	no children	2.4%	5.8%	1.6%	27.0%	3.9%	8.3%	3.2%	39.0%
	1 child	4.5%	2.6%	0.4%	14.8%	6.1%	4.9%	1.7%	35.8%
	2 children	3.9%	6.7%	2.8%	42.3%	5.8%	10.8%	6.2%	57.2%
	3+ children	8.8%	17.4%	4.5%	25.7%	10.6%	21.3%	8.5%	39.8%
Marital status*	Single	3.6%	5.7%	1.0%	18.3%	6.2%	9.0%	3.0%	32.7%
	Couple	3.4%	6.0%	2.2%	36.1%	4.6%	8.7%	4.5%	51.2%
	Divorced	5.3%	10.0%	2.0%	20.2%	7.4%	13.5%	4.4%	32.6%
	Widowed	1.0%	1.0%	0.0%	0.0%	1.0%	1.0%	0.0%	0.0%
Education level*	Low (ISCED=0,1,2)	5.4%	10.7%	5.0%	46.4%	8.5%	19.0%	10.3%	54.4%
	Middle (ISCED=3,4)	4.3%	10.6%	1.9%	18.1%	6.2%	14.9%	5.3%	35.2%
	High (ISCED=5,6)	1.8%	2.1%	0.9%	43.0%	2.3%	2.4%	1.3%	54.5%
Employment status*	Employed	3.0%	4.0%	0.8%	20.3%	4.8%	7.1%	2.9%	40.5%
	Self-Employed	2.8%	10.2%	3.6%	35.8%	6.4%	14.8%	5.3%	36.0%
	Unemployed	8.5%	7.5%	1.5%	20.4%	8.7%	8.0%	2.7%	33.9%
	Retired	4.4%	16.2%	4.1%	25.6%	4.5%	16.6%	7.6%	46.0%
	Other not working	6.8%	19.6%	10.4%	53.0%	8.7%	20.9%	13.8%	65.8%
Housing status	Owner-outright	0.7%	1.5%	0.0%	0.0%	0.7%	1.8%	0.3%	16.9%
	Owner-with mortgage	3.3%	6.5%	2.0%	30.3%	5.8%	10.1%	4.4%	43.2%
	Renter or other	6.6%	9.4%	2.5%	26.7%	7.9%	9.9%	4.8%	48.8%
Total gross income	Quintile 1	10.5%	14.9%	4.1%	27.6%	14.2%	21.3%	8.4%	39.6%
	Quintile 2	4.0%	12.5%	2.0%	16.3%	5.9%	16.8%	5.7%	34.0%
	Quintile 3	1.7%	4.5%	2.0%	45.6%	2.9%	7.5%	3.2%	43.2%
	Quintile 4	1.7%	5.7%	1.8%	31.0%	2.9%	9.3%	5.3%	56.5%
	Quintile 5	0.3%	2.5%	1.0%	42.1%	0.4%	3.1%	1.5%	48.6%
Total net wealth	Quintile 1	9.2%	12.3%	7.1%	58.0%	11.6%	16.8%	12.0%	71.4%
	Quintile 2	5.0%	8.3%	2.5%	29.5%	8.7%	13.8%	6.5%	47.5%
	Quintile 3	1.0%	1.3%	0.2%	18.4%	1.7%	2.1%	0.4%	21.1%
	Quintile 4	2.1%	9.9%	1.6%	15.9%	2.7%	11.1%	3.9%	35.4%
	Quintile 5	0.9%	2.9%	0.1%	2.0%	1.8%	5.5%	0.5%	8.6%

Source: Own calculations based on the 2nd wave of the LU-HFCS. Data are multiply imputed and weighted. We use the financial margin 1 (household-specific food & utilities). Personal characteristics indicated by an asterisk refer to the "financially knowledgeable person" (FKP).

Acknowledgements

This paper should not be reported as representing the views of the BCL or the Eurosystem. The views expressed are those of the authors and may not be shared by other research staff or policymakers in the BCL, the Eurosystem or the Eurosystem Household Finance and Consumption Network. We give special thanks to Paolo Guarda for his valuable advice, his detailed suggestions and helpful comments. In addition, we thank Stephan Fahr (discussant), Patrick Fève, Bob Kaempff, Abdelaziz Rouabah, Cindy Veiga, two ECB referees and participants at a BCL internal seminar and the extended ECB research seminar for useful comments.

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PDF ISBN 978-92-899-3516-6 ISSN 1725-2806 doi:10.2866/357791 QB-AR-19-035-EN-N