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The effectiveness of borrower-based macroprudential policies: a cross-country analysis using an integrated micro-macro simulation model

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Abstract

This paper evaluates the resilience benefits of borrower-based macroprudential policies—such as LTV, DSTI, or DTI caps—for households and banks in the EU. To that end, we employ a further developed variant of the integrated micro-macro simulation model of Gross and Población (2017). Besides various methodological advances, joint policy caps are now also considered, and the resilience benefits are decomposed across income and wealth categories of borrowing households. Our findings suggest that (1) the resilience of households improves notably as a result of implementing individual and joint policy limits, with joint limits being more than additively effective; (2) borrower-based measures can visibly enhance the quality of bank mortgage portfolios over time, supporting bank solvency ratios; and (3) the policies' resilience benefits are more pronounced for households located at the lower end of the income and wealth distributions.

JEL codes: C33, E58, G18

Keywords: Borrower-based macroprudential policy, household micro data and modeling, macro-financial linkages.

Non-Technical Summary

This paper contributes to advancing the development of quantitative tools for assessing the role of borrower-based macroprudential policy measures (BBMs) in enhancing borrower and bank resilience and leaning against the build-up of macro-financial imbalances in general and, with regard to vulnerabilities, in real estate markets specifically. BBMs have been increasingly implemented across European Union (EU) countries and have also been recommended by the European Systemic Risk Board (ESRB) in the context of the discussions on residential real estate vulnerabilities and the appropriate macroprudential policy response. Quantitative tools for policy assessment are essential in the context of the European Central Bank's (ECB) responsibilities for the coordination and co-shaping of macroprudential policies in the euro area.

The model methodology employed in this paper is an enhanced, further refined version of the micro-macro simulation approach of Gross and Población (GP, 2017). It is used to analyze the effectiveness of BBMs, including across different parts of the income and wealth distributions, which was not yet addressed in GP (2017). The model is used here to conduct an *ex-ante* BBM policy assessment across countries. The model helps to quantify the extent to which borrower-based measures such as caps on loan to value (LTV), debt to income (DTI), debt service to income (DSTI) ratios as well as their joint application enhance the resilience of households and banks, as measured by probabilities of default (PD) and loss given default (LGD), both defined in a manner compatible with bank accounting and regulation. The model captures numerous economic transmission mechanisms for such policies, in a structural simulation framework rooted in micro and macro data. It is, hence, instrumental for informing policy makers on the basis of empirically relevant policy counterfactual analysis.

The model results for 19 EU countries suggest that borrower-based macroprudential policies are effective across four policy-relevant dimensions. First, household PDs and LGDs are found to improve notably when implementing BBMs, with the effect being stronger—and more than additive—when policy caps on LTV, DSTI and DTI are applied jointly. Second, the model captures the policy-induced drag on loan demand which in turn impacts economic growth, employment, interest rates, and house prices. These short-term effects may be interpreted as short-term costs under an expansionary macroeconomic scenario, in the sense of resulting in moderately increasing PDs and LGDs, while the net policy effect on PDs and LGDs remains positive (i.e., they fall). Third, the counterfactual impact of BBMs on bank capital ratios is found to be economically relevant for many European banking systems, through banks' mortgage loan portfolios, reflecting the improving credit risk parameters (via expected and unexpected losses). Fourth, the policy-induced reduction in PDs is found to be stronger for households below the median of the income and net wealth distributions, which points to important distributional effects that policy makers ought to be aware of.

1. Introduction

This paper aims to evaluate the effectiveness of borrower-based macroprudential policies in supporting the resilience of households and banks, utilizing an integrated micro-macro model framework. Building on the integrated dynamic household balance sheet (IDHBS) model of Gross and Población (2017), our model framework quantifies the extent to which borrower-based measures (BBMs), including their joint application, enhance the resilience of households and banks. Often used in conjunction and applied in residential real estate markets, limits to loan to value (LTV), debt to income (DTI), and debt service to income (DSTI) ratios enhance households' resilience to economic downturns, in addition to containing credit growth and household indebtedness during an economic upturn. Borrower-based policies are meant to improve the quality of banks' mortgage loan portfolios through more prudent lending standards. The lower risk of banks' household exposures promotes the resilience of banks during periods of economic downturns, which supports banks' lending capacity and economic activity during recessions more broadly, and thereby should overall lessen macro-financial feedback effects.[1]

BBMs have been implemented in many jurisdictions in the European Union (EU).[2] The increasingly frequent use of BBMs has led to the development of frameworks and methodologies for assessing their effectiveness as part of the broader toolkit of macroprudential policies aiming to counteract the build-up of risk in residential real estate markets.[3] Among these methodologies, descriptive analyses examine the distribution of lending standards, targeting a distribution profile consistent with a risk tolerance threshold while assessing market access issues for certain borrower categories as well as the amount of mortgage credit restricted. Empirical micro assessment methods link credit risk parameters with lending standards at origination, while standalone macro empirical approaches look at the macroeconomic impact of the policy induced credit restrictions. More recently, more advanced integrated micro-macro approaches focus on the resilience benefit of BBMs measured as the policy-induced reduction in credit risk while also accounting for the macroeconomic feedback from constraining credit associated with the behavioral response of mortgage borrowers.

Within this latter class of methods, our semi-structural micro-macro model framework simulates the behavior of borrowing households and the associated dynamics of credit risk parameters with and without imposing BBMs. The model captures the dynamics of household debt service and consumption expenditure alongside labor income and unemployment benefits, depending on household members' simulated employment status. The primary model outputs

[1] For a broader discussion of the effectiveness of macroprudential policy see Ampudia et al. (2021), which also includes a preliminary version of the results presented herein.
[2] See Chapter 5 of the ECB Financial Stability Report November (2019) and the ESRB report on vulnerabilities in the residential real estate sectors of the EEA countries (2022)
[3] See the report of the ESRB working group on methodologies for the assessment of vulnerabilities and macroprudential policies for residential real estate (2019).

are individual households' simulated probability of default (PDs) and loss given default (LGDs) which are subsequently attached to bank mortgage portfolios to obtain their capital impact. The model also accounts for macro-financial feedback of policies, which result from their drag on credit demand.

Our work expands on the initial framework of GP (2017) in several ways. First, we introduce a separate DTI limit and implement the evaluation of joint caps, based on all or a subset of LTV, DSTI, and DTI caps. Second, we introduce an alternative model scheme for the borrower response to policy caps—to which we refer as "borrow at the cap"—to reflect the impact of policies on new lending volumes. Compared to a "full crowding out" approach from the original framework, the alternative constrains the new lending only up to the policy limit (as opposed to excluding a prospective borrower from the market when the policy limit was binding). Third, deposit rates determining households' interest income as well as insurance and pension savings are now endogenized and linked to short-term interest rates, as are lending rates for variable rate contracts as a function of short-term interest rates. Fourth, we distinguish between fixed and variable rate loan contracts, including a more realistic nonlinear repayment schedule for the latter. Fifth, a distinction between an "accounting mode" and an "economic mode" is introduced for the LGD module. Sixth, the GVAR macro core from the original framework has been replaced by country-specific SVARs, as the current application is not primarily focused on cross-border spillover effects.[4]

We find that BBMs are effective across four policy dimensions. First, when assessing the impact of policies on household PDs, LGDs and their product (the loss rate, LR), we find that these metrics improve notably when implementing BBMs, with the effect being stronger—and more than additive—when policy limits on LTV, DSTI and DTI are applied jointly. Second, we account for the policy-induced drag on loan demand which exerts feedback to GDP growth, employment, interest rates, and house prices. Because these short-term second round effects result in moderately increasing PDs and LGDs, they may be interpreted as short-term costs under an expansionary macroeconomic scenario. However, the policies effectively provide a benefit from a longer-term perspective by rendering economic dynamics more stable over time. Third, we find the impact of BBMs on the capital ratios of banks to be notable for many European banks, through their mortgage loan portfolios reflecting the improving credit risk parameters (via expected and unexpected losses). Fourth, the policy-induced reduction in PDs is found to be stronger for households below the median of the income and net wealth distributions, which points to important distributional aspects that policy makers should be aware of.

[4] Numerous model features are detailed in a companion paper (Gross et al., 2022) which uses the enhanced model framework to analyze the determinants of mortgage default rates in EU countries and the US. It focuses on scenario-conditional forecasting and fiscal policy counterfactuals, including with a view to COVID-19 support policies such as debt moratoria. The present paper emphasizes instead the evaluation of macroprudential policies and the wealth and income distribution-dependent credit risk effects.

2. Literature

The paper relates to the literature in several ways.

First, by attributing high relevance to credit dynamics (household debt for what concerns the focus of this paper) that shape macro-financial outcomes, our work relates to empirical work by Mian and Sufi (2009) and Jòrda et al. (2013, 2016). The turning point analysis of Claessens et al. (2010) confirms that recessions are typically preceded by credit and housing booms. Similarly, based on cross-country panel data, Schularick and Taylor (2012) conclude that booms in credit and housing are strong predictors of subsequent recessions.

Second, by focusing on the impact of BBMs on household risk metrics (PDs and LGDs) in a micro-macro simulation framework, our paper links to the growing literature that uses micro data and/or micro (-macro) simulation frameworks to assess borrower-based macroprudential policies (Cussen et al. 2015, Gross and Población 2017, Nier et al. 2019, Jurča et al. 2020, Neugebauer et al. 2021, Dirma and Karmelavičius 2023).[5]

Further, our paper relates to the empirical literature on the impact of macroprudential policies on macroeconomic dynamics. Numerous papers assess the impact of macroprudential policies on house prices and credit (Lim et al. 2011, Ahuja and Nabar 2011, Jacome and Mitra 2015, Kuttner and Shim 2016, Richter et al. 2018, Poghosyan 2019). Some of these find that aggregate house price dynamics and LTV distributions appear to be related (Almeida et al. 2006, Crowe et al. 2011). Others suggest that a tightening of LTV caps can curb borrower leverage and foster bank resilience to house price shocks (Ahuja and Nabar 2011, Wong et al. 2011, Funke and Patz 2012).

Our paper contributes to the examination of distributional effects of macroprudential policies. Several papers assess the potential negative welfare effects of BBMs in terms of wealth and income inequality, as possibly stemming from the potential exclusion of low-income households from the mortgage market. For instance, Carpantier et al. (2016) find that higher (i.e., less stringent) LTV caps are associated with more wealth inequality. Frost and Stralen (2018) find a positive relationship between LTV limits and net income inequality. Georgescu and Martin (2020) conclude that BBMs have a moderate negative welfare impact in terms of wealth inequality and a negligible impact on income inequality. While we do not conduct a formal assessment of BBMs on inequality metrics, we interpret the relatively stronger resilience gain due to BBMs for borrowers at the lower end of the income/wealth distributions as a financial stability benefit, as they contribute to disincentivizing more vulnerable borrowers from excessive risk taking.

[5] Jurča et al. (2020) and Gross et al. (2022) present a more comprehensive literature review, which should be a useful complement to the brief overview provided here.

3. Data and Methodology

3.1 Data and Model Inputs

The model requires three types of data inputs (household micro, macro, and banking-related) along with a set of calibrated parameters. The micro data are sourced from the Household Finance and Consumption Survey (HFCS) which collects comprehensive information at the household and household member level.[6] The macro data were collected from the data warehouses of the ECB and the OECD.

The third HFCS wave (of 2017) was used as an anchor for the model which covers 19 EU countries. Variables required from the HFCS include principal mortgage debt outstanding and values of real estate property at origination but also current values of consumer debt, real estate property, liquid financial assets (at the household level) as well as employment status, income, and various sociodemographic characteristics, the latter all at the level of individuals (Table 1). The country-specific distributions of mortgage volumes are shown in Figure 1.

The lending standards subject to BBMs are defined using the HFCS data on household debt, property values, and household income. We employ common definitions for the LTV, DSTI, and DTI ratios across countries (Table 2). For comparability, we disregard some differences from definitions adopted by country authorities in practice in some cases. Figure 2 visualizes the country-specific distributions of the lending standard indicators computed from the HFCS data.[7]

Macroeconomic and banking system data are used for the respective modules. Our quarterly macro-financial database comprises six variables for 19 EU countries over the 1995Q1-2017Q4 period. They include the unemployment rate, compensation per employee, residential house prices, stock prices, 3-month money market rates, and credit to the nonfinancial private sector. Banking system parameters related to risk weighted assets, CET1 capital, the share of IRB mortgages in total mortgage portfolios, nonperforming loans, and PDs and LGDs are drawn from various additional sources (Tables 3 and 4). The definitions of the parameters for the micro and macro modules and their respective calibration are summarized in Tables 5 and 6.

3.2 Model Framework

The model integrates three modules: a macro module, a micro simulation module, and a bank impact module. Figure 3 provides two schematics of the model framework (one being somewhat more technical than the other). A structural VAR (SVAR) model is involved to generate a large number of simulated forward paths for the macro-financial variables. A logistic

[6] Details regarding the HFCS micro data can be found under Household Finance and Consumption Network (HFCN).
[7] For a discussion on the progress with the harmonization of definitions and indicators used for monitoring residential real estate markets, see the ESRB Summary Compliance Report (2021).

regression model is used to determine the probability of household members being employed. When integrated in the model suite, an intercept shift is considered to match an aggregate unemployment rate path from the macro module, to then simulate the employment status of household members accordingly. Multiple forward distributions representing a baseline macroeconomic scenario are produced from the country specific SVARs and integrated with the micro module to produce forward simulations of households' P&L and implied balance sheets. A rule for default detection compares the debt service of households (net of the cost of living) with income flows and changes in financial assets to identify default events which result in simulated PDs and LGDs. These parameters are attached to the mortgage exposures of banks to obtain estimates for their capital impact.

The transmission of BBMs to household borrowers and the economy at large is captured in two steps. In a first round, the regulatory limits on LTVs, DSTIs, DTIs and the joint limits, restrict new high-risk lending ("borrow-at-the-cap"). Under the baseline macroeconomic scenario, this reduces the frequency of default events by supporting repayment capacity and consequently improving PDs and LGDs. However, directly constraining the flow of new mortgage credit entails a short-run macroeconomic cost.[8] The constraint is fed back into the framework via a policy-induced negative credit demand shock identified with sign restrictions (scaling the policy-induced new mortgage volume cuts into a corresponding aggregate credit reduction in the macro module). This shock puts downward pressure on the baseline house prices and income and consequently can increase the PDs and LGDs compared to the first round. The net policy effect is represented by the combined impact on the household credit risk parameters from both rounds.

The impact of BBMs on banks' capital adequacy ratios is obtained by "attaching" the estimated mortgage PDs and LGDs to the mortgage portfolios of banks. The model quantifies the impact through changing expected losses on the stock of capital as well as through changing risk weights on risk weighted assets. The latter differentiates between the bank- or banking system-specific portion of banks' household credit portfolio treatment under the Basel Standardized (STA) vs. the Internal Rating Based (IRB) approach.

3.3 The Model

A. The Macro-Module

The macro module is based on a Structural Vector Autoregressive (SVAR) model structure (Bernanke 1986, Blanchard and Watson 1986, Sims 1986):

$$AY_t = B(L)Y_{t-1} + \varepsilon_t \,, \qquad (1)$$

[8] The cost or benefit *interpretation* of the reduced new mortgage lending (as well as the associated deceleration in house prices) is conditional on the underlying macroeconomic scenario.

where Y_t is the vector of the following six endogenous variables: the unemployment rate (URX), compensation per employee growth (CPE), residential house price growth (RHP), stock price growth (ESX), 3-month money market rates (IR3M), and growth of credit to the non-financial private sector (CRE). For CPE, RHP, ESX, and CRE, quarter-on-quarter log differences are used.

The elements of the (square) matrix A are the structural parameters on the contemporaneous endogenous variables (thus A characterizes the contemporaneous relationships among the variables in the VAR), and B(L) is a p-th degree matrix polynomial in the lag operator L, that is, $B(L) = B_0 + B_1 L + B_2 L^2 + \ldots + B_p L^p$, where all of the B matrices are square.[9]

The SVAR model (1) can be written as a reduced-form VAR model:

$$Y_t = C(L) Y_{t-1} + e_t \quad , \tag{1'}$$

where:

$$C = A^{-1} B \qquad \text{and} \qquad e_t = A^{-1} \varepsilon_t \; .$$

Equation (1') contains the structural relations of the model, linking the reduced form errors e_t to structural shocks ε_t linearly by the 6×6 structural impact matrix A^{-1}, which implies a reduced form error covariance matrix $\Sigma_e = (A^{-1})' A^{-1}$. We can obtain estimates for the matrix C by estimating Model (1') through OLS. To form estimates for A^{-1}, we operate with sign restrictions.

The estimated SVAR model for a chosen country allows us to generate a large number of simulated forward paths for the six endogenous macroeconomic variables. This multi-variate, multi-period density forecast of the endogenous variables drives the micro simulation of individual household balance sheets to obtain the distributions of simulated PDs and LGDs. The macro simulations involve a parametric bootstrap, drawing from the estimated coefficients (of matrix C in equation (1')) along with residual draws from a multivariate normal distribution with zero mean and the residual variance-covariance matrix from the SVAR.

The country-level forward paths of the macroeconomic variables are utilized in the micro-module of our model to steer the following household and household member-level variables:

- The unemployment rate (URX) variable is used in the *employment status simulator* (described in Section B.1) to obtain forward paths of the employment status for all household members (eq. 3).
- The compensation per employee (CPE) variable is used to steer the income path for employed household members in the *household balance sheet simulator* (described in

[9] For simplicity, we assume that p=1.

Section B.2). Log percent changes of income from the SVAR are attached to the household members' quarterly income starting points (eq. 4).

- Stock prices (ESX) are used to re-value the stock holdings of a household (pooled from household members) in the *household balance sheet simulator* (Section B.2). Log percent changes of equity prices from the SVAR are attached to the household level value of stocks at the survey date (eq. 7).

- The 3-month money market rate (IR3M) is used to steer the value of bond holdings of the households in the *household balance sheet simulator* (Section B.2). Absolute quarter-on-quarter changes of interest rates are used to re-compute the market value of the bonds (eq. 8). This variable is also used to steer the variable interest rate (eq. 12) which we need to model the interest expenses of the debt service flow for consumer and/or mortgage debt (eq. 13) and also the discount factor of the LGD module (eq. 17).

- Residential house prices (RHP) are used to obtain projections for households' housing collateral sales values which constitute an integral part of LGD as a component of the *household balance sheet simulator* (Section B.2, eqs. 16 and 18).

The macro module is also used to produce sign-restricted impulse responses to a shock to NFPS credit growth. The negative credit demand shock is subsequently re-scaled to the level implied by a user-defined borrower-based policy limit to obtain the policy impact on the macro-financial variables and the second round (macro feedback) effects on the household risk metrics. The sign constraints identifying a negative credit demand shock are [1 -1 -1 -1 -1 0] for the six endogenous variables URX, CPE, RHP, ESX, IR3M, CRE, where 1 denotes a positive constraint, -1 a negative one, and 0 no constraint.

B. The Micro-Module

B1) Employment Status Simulator

The employment status simulator generates paths of the employment status for all individuals which will determine household income.[10] The simulation of the employment status of household members (HMs) starts from the current employment status indicated in the survey. It is driven forward by the predicted employment probabilities from the logistic regression model estimated on HFCS data, consistent in each simulation period with the path for aggregate unemployment implied by the macro module.

[10] Retirees are included in the model, for whom PDs and LGDs are estimated as for the rest of the debt-holding population. While retirees are generally unlikely to default on their debt because of their stable income (from public or private and occupational pensions), they could in principle still experience debt service problems if they hold variable interest rate loans and have relatively small savings. Hence, while they are excluded from the employment status models and stochastic employment simulations, they form part of the household sample whose PDs and LGDs are simulated in the next submodule.

The country-specific logistic regression models for the employment status include as explanatory variables the following household member characteristics: age, gender, marital status, the highest level of education completed, and whether the household member has its origin in the same country or not. The estimation results for the country-specific logit models can be found in Appendix A.

From the logistic models, we obtain the probability of being employed for a household member hm, PE_{hm}, as follows:

$$PE_{hm} = \frac{1}{1+e^{-\left(\beta_0+\sum_{i=1}^{I}\beta_i x_i^{hm}\right)}} \quad , \tag{2}$$

where x_i^{hm} denotes the explanatory variables of the logistic models (with the subscript *i* denoting the household member characteristic), while the β_i's are the corresponding regression coefficients.

The simulated paths of individuals' employment status are generated consistently with the population-level unemployment rate paths. Letting $U_{hm,j}^{HFCS}$ denote the unemployment status for household member hm of country *j* in the survey ($U_{hm,j}^{HFCS}$ is 1 if individual hm is unemployed and 0 otherwise), $URX_{j,t}^{Macro}$ be the simulated unemployment rate (URX) of country *j* at period *t* from the SVAR model of the macro module, and $PE_{hm,j}^{Logit}$ be the predicted probability of being employed for household member hm in country j from the logistic model, and $U_{hm,j,t}^{Sim}$ the stochastic forward path of the employment status for individual hm in country *j* at period *t*, we simulate the paths of the employment status for all individuals as follows:

- We set as a starting point the employment status according to the HFCS data $U_{hm,j}^{HFCS}$. That is, $U_{hm,j,t_0}^{Sim} = U_{hm,j}^{HFCS}$.
- For period *t*, we calculate the deviation between the unemployment rate of country *j* implied by the HFCS sample of household members (HMs) in that country and the aggregate unemployment rate implied by the simulated macro series from the macro module:

  $$deviation_t^j = \sum_{hm=1}^{N_j} U_{hm,j}^{HFCS} - URX_{j,t}^{Macro}, t = t_0, \ldots, T \quad , \tag{3}$$

  where N_j denotes the number of HMs in country *j*.

  A $deviation_t^j > 0$, implies that the aggregate unemployment rate of the HMs is larger than that the one resulting from the macro model, so we have to adjust (reduce) the number of the unemployed HMs.
- Using random draws from the uniform distribution in the interval [0,1], we assign an individual the employment flag whenever the uniform random number is larger than its estimate for the probability of being employed.
- We repeat steps 1-4 until we achieve a zero deviation.

B2) The Household Balance Sheet Simulator

The household balance sheet module uses the micro and macro module inputs to detect defaults and compute PDs and LGDs. The household balance sheet module operates at the household-level, i.e., the household member information coming from the employment simulator is combined by assigning household members to their households.

The evolution of a household's h financial assets (FA) is determined as follows:[11]

$$\Delta(FA)_{h,t} = EI_{h,t} + II_{h,t} + OI_{h,t} + \Delta B_{h,t} + \Delta S_{h,t} - CE_{h,t} - OE_{h,t} - A_{h,t}^{T} \ , \tag{4}$$

where $EI_{h,t}$ denotes the employment income (or unemployment benefit), $II_{h,t}$ the interest income on deposits, $OI_{h,t}$ other income (e.g. child benefit, alimony, etc.), $\Delta B_{h,t}$ and $\Delta S_{h,t}$ the change in the market value of bonds and outstanding shares, respectively, $CE_{h,t}$ the consumption expenses, $OE_{h,t}$ other expenses (e.g. rent), and $A_{h,t}^{T}$ the debt service flow for consumer and mortgage debt of type $T \in \{fixed, variable\}$, to distinguish between fixed and variable rate debt. The periodic change in financial assets (eq. 4) has implications for the default event which is determined in eq. (14).

The employment income or unemployment benefit $EI_{h,t}$ is given by:

$$EI_{h,t} = \begin{cases} INC_{N,t}^{E} \times (1 - tax_c), & \text{for employed household members} \\ INC_{N,t}^{U}, & \text{for unemployed household members} \end{cases} , \tag{5}$$

where N counts the number of HMs in a HH. We separate HMs between employed and unemployed according to their simulated forward employment status from the employment simulator (submodule B1). The employment income, $INC_{N,t}^{E}$, comes from the HFCS dataset, whilst the unemployment benefit, $INC_{N,t}^{U}$, is obtained by applying a country-specific replacement rate to the HH members' most recent gross employment income $INC_{N,t}^{E}$, subject to an absolute ceiling that is informed by country-specific legislation and the maxima and upper percentiles in the micro dataset itself.

Other income, $OI_{h,t}$, is obtained from the HFCS data, whilst the deposit interest income, $II_{h,t}$, is given by:

$$II_{h,t} = \frac{1}{4} \times Dep_{h,HFCS} \times DPR \ , \tag{6}$$

where $Dep_{h,HFCS}$ denotes the household's deposits (obtained from the HFCS dataset) and DPR the (exogenous) deposit rate, properly adjusted to include the pass-through from money market rates to deposits rates.

[11] To keep the notation lean, we omit the superscript j (denoting the country) from the equations from this point forward.

Households' bond and stock holdings are revalued based on the interest rate and stock price paths. The value of household's *h* share holdings ($S_{h,t}$) is given by:

$$S_{h,t} = e^{ln[S_{h,t-1}+\Delta(ESX_t^{sim})]} \ , \tag{7}$$

where $\Delta(ESX_t^{sim})$ is the periodic change in the simulated stock prices growth from the macro module.

A modified duration approach is used to revalue their bond holdings ($B_{h,t}$), assuming a $\mathrm{D} = 2$-year average bond duration:[12]

$$B_{h,t} = \left[1 - \frac{D}{1+i_{t-1}^{sim}} \times \Delta i_{t-1}^{sim}\right] \times B_{h,t-1} \ \ , \tag{8}$$

where i_t^{sim} is the simulated 3-month money market rate (IR3M) from the macro module.

The consumption ($CE_{h,t}$) and other ($OE_{h,t}$) expenditures variables are obtained from the HFCS dataset.[13]

The debt service flow for consumer and/or mortgage debt in eq. (4), $A_{h,t}^{T}$, comprises interest expenses and principal repayment of mortgage debt and consumer debt. The model distinguishes between fixed ($A_{h,t}^{fixed}$) and variable ($A_{h,t}^{var}$) rate debt. The information about the interest rate type of HHs' individual outstanding debt contracts is contained in the microdata and used in the model. Since the interest and principal flow calculations are conducted at a monthly frequency, we are denoting the monthly time steps in the equations that follow by *m* to distinguish them from quarterly steps, denoted by q, elsewhere in this section.

A nonlinear repayment schedule is designed for all debt-holding households. The initial (at period t_0) residual duration *M* in *months* of the "synthetically combined" debt (mortgage plus consumer debt) for each debt-holding household is first approximated as a function of the HFCS-reported HH-level loan-specific annual interest rate $\mathrm{i}_{\mathrm{h},HFCS}$, the currently outstanding principal debt stock $\mathrm{P}_{\mathrm{h},HFCS}$, and the current quarterly annuity flow, $A_{h,HFCS}$, as follows:

$$M_{h,t_0} = \frac{log\left(\frac{4\times A_{h,HFCS}}{4\times A_{h,HFCS} - i_{h,HFCS}\times P_{h,HFCS}}\right)}{log\left(\frac{i_{h,HFCS}}{12}+1\right)} \ . \tag{9}$$

For *fixed rate loans*, the monthly interest payment flow, $A_{h,t+m}^{I,fixed}$, and their monthly principal repayment flows, $A_{h,t+m}^{P,fixed}$, are:

[12] The choice of the average duration parameter has only a negligible impact on the results, because HHs' bond holdings are small in all countries.
[13] Our model framework provides two more options for the consumption expenditure process. See Gross et al. (2022) for more details.

$$A_{h,t+m}^{I,fixed} = \frac{i_{h,HFCS}}{12} \times P_{h,t+m-1} \;\; and \;\; A_{h,t+m}^{P,fixed} = A_{h,t+m}^{fixed} - A_{h,t+m}^{I,fixed} \,, \tag{10}$$

where $P_{h,t+m}$ is the principal debt balance that falls by the monthly principal repayment flow: $P_{h,t+m} = P_{h,t+m-1} - A_{h,t+s}^{T,P}, T \in \{fixed, variable\}$.

For *variable rate* loans, the monthly interest payment flow, $A_{h,t+m}^{I,var}$, is a function of a variable interest rate path, $i_{h,t+m-1}$:

$$A_{h,t+s}^{I,var} = \frac{i_{h,t+s-1} \times P_{h,t+s-1}}{12} \,, \tag{11}$$

where a variable rate loan's $i_{h,t+m-1}$ evolves endogenously in parallel to the simulated 3-month interest rate from the macro module, i_{t+m}^{sim}, as follows:

$$i_{h,t+m} = max\left(0, i_{h,t+m-1} + \Delta i_{t+m}^{sim}\right) . \tag{12}$$

The total monthly annuity for *variable rate* loans, $A_{h,t+m}^{var}$, and the principal repayment flow, $A_{h,t+m}^{P,var}$, are computed every month as:

$$A_{h,t+m}^{var} = P_{h,t+m-1} \frac{\frac{i_{h,t+s}}{12}\left(1+i_{h,t+m}/12\right)^{M_{h,t+m}^{res}}}{\left(1+i_{h,t+m-1}/12\right)^{M_{h,t+m}^{res}}-1} \;\; \text{and} \;\; A_{h,t+m}^{P,var} = A_{h,t+m}^{var} - A_{h,t+m}^{I,var} \,, \tag{13}$$

where $M_{h,t+m}^{res}$ is the residual maturity in months, which evolves as $M_{h,t+m}^{res} = M_{h,t+m-1}^{res} - 1$. The interest and principal flow calculations are conducted at a monthly frequency, but then converted to quarterly to be compatible with the quarterly frequency of the model simulation. This entails taking sums of principal and interest payment flows in non-overlapping steps of three months going forward in time.

The default rule is defined via the following indicator for a household h:

$$Default \; in \; t+q := \begin{cases} 1, if FA_{h,t+q} < 0) \\ 0, otherwise \end{cases} . \tag{14}$$

If the stock of financial assets become negative, i.e., when net income flows do not suffice to keep cash stocks positive and debt serviceable, in some period along the simulation horizon, the household is assigned a default flag. Once a household receives the flag, we stop simulating the household and its members' income and expenses assuming the household cannot recover and resume its debt repayment.

The *probability of default (PD)* for a household h is defined as:

$$PD_h = \frac{number \; of \; defaults \; of \; household \; "h" \; across \; paths}{total \; number \; of \; paths} . \tag{15}$$

Various components of financial assets, $FA_{h,t}$, are functions of the endogenous macroeconomic variables of the macro module, for which a large number of simulation paths are provided. These paths feed through to the PDs and LGDs, at the household level, for which full distributions are therefore obtained.

Along with the default indicator, *losses given default (LGD)* are computed for all households at each point in time along the simulation horizon (we denote this point by t_0 in the following). The LGD module relates the house value to a house price path. First, each household's predicted housing collateral sales value, V_{h,t_0+Q}, at the future time of resolution ($t_0 + Q$ quarters), is projected in line with a simulated forward path for quarter-on-quarter log house price growth (RHP_t^{sim}) obtained from the macro module. A household-specific claim that a bank attempts to recover is denoted as $\mathrm{Claim_h}$. *C* captures administrative and legal costs measured as a percentage of outstanding principal, and $i_{h,t_0}^{MORT,eff}$ is the effective mortgage loan interest rate at the household-level (obtained from the survey data). With these terms, the nominal *expected recovery value,* ERV_h, can be defined as:

$$ERV_h = min\,(\underbrace{exp\left(ln(V_{h,t_0}) + \sum_{q=1}^{Q} RHP_{t=q}^{sim}\right)}_{V_{h,t_0+Q}}, \underbrace{\left(1 + C + 0.25 \times i_{h,t_0}^{MORT,eff}\right) P_{h,t_0}^{MORT}}_{Claim_{h,t_0}}). \quad (16)$$

The inclusion of a quarter of the annual effective mortgage rate in the claim term reflects that interest payments over 90 days (three months) were missed and are capitalized by assumption. The minimum operator around the two terms in eq. (16) reflects bankruptcy law, which generally stipulates that if the recovery value exceeds an outstanding claim, the difference must be credited back to the defaulted borrower.

A time-varying expected return measure for mortgages at the country level, R_{t_0}, is used for discounting in the LGD module. R_{t_0} is assumed to move parallel to the 3-month interest rate (i_{t}^{sim}) simulated by the country-specific SVAR model in the macro module, as follows: $i_{t_0+q}^{MORT,eff} = i_{t_0}^{MORT,eff} + i_{t_0+q}^{sim} - i_{t_0}^{sim}$.

The discount factor for mortgage-holding households is defined as:

$$DF_h = \left(1 + \frac{\overline{i_{t=1,\dots,Q}^{MORT,eff}}}{12}\right)^{-3Q}, \quad (17)$$

where the term $\overline{i_{t=1,\dots,Q}^{MORT,eff}}$ is the average of the expected return path along the horizon up to resolution time.[14]

The LGD for household *h* is computed as:

[14] The model offers an alternative approach for computing the discount factor. See Gross et al. (2022) for more details.

$$LGD_h = (1 - CP) \times \left(1 - \frac{DF_h \times ERV_h}{Claim_h}\right), \tag{18}$$

where CP is an exogenous country-specific cure probability (see Table 5).

Once the PDs and LGDs are generated at the household-level, they can be aggregated to the population-level for each country j:

$$PD_j = \frac{\sum_{h=1}^{H_j} [PD_h \times L_h]}{\sum_{h=1}^{H_j} L_h}, \tag{19}$$

$$LGD_j = \frac{\sum_{h=1}^{H_j} [LGD_h \times L_h]}{\sum_{h=1}^{H_j} L_h}, \tag{20}$$

where L_h denotes the current outstanding mortgage debt for household h in country j and H_j the number of households in country j.

The Loss Rate (LR) of country j is given by the product of country-level PD and LGD:

$$LR_j = PD_j \times LGD_j . \tag{21}$$

C. The Bank Impact Module

The bank impact module "attaches" the simulated PDs and LGDs from the micro module to the mortgage portfolios of banks and computes the implied bank capital ratio impact. We assume a 100 percent pass-through of the simulated PDs and LGDs into the regulatory credit risk parameters associated with the mortgage loan exposures of banks. This parameterization implicitly assumes a sufficient time for the effect of BBMs, which are applied on new mortgage flows, to translate into more resilient mortgage stocks. The analysis is conducted at the national banking system level but can also be applied at individual bank level.

The risk-weighted capital ratio of the banking system of country j at year t is given by:

$$\text{CET1Ratio}_{j,t} = \frac{[CET1_{j,t_0} - \sum_{s=1}^{t} ProvFlows_{j,s} + \sum_{s=1}^{t} MII_{j,s}]}{RWA_{j,t_0} + \Delta(RWA)_{j,t}} . \tag{22}$$

The expression involves the selected flows impacted by BBMs which we consider here, that is, (smaller) loan loss provision flows and (forgone) interest income flows, related in either case to mortgage loan portfolios. The *CET1 ratio* is computed forward in time, both for a reference, no-policy scenario and under BBM policies to yield the capital ratio impact of the BBMs. The differential effects of provision flows ($ProvFlows$), mortgage interest income (MII), and changes in risk weighted assets (RWA) can then be examined. The calculation looks only at the impact of BBMs via risk parameters and does not take a view with respect to possible uses of internal capital generation capacity (related to the provision and interest income flows).

The relevant data sources for the components of the banking module (i.e., the initial values of the variables and the banking system parameters) can be found in Table 3.

The volumes of the total (ML_j), the performing (PML_j) and the non-performing mortgage loans ($NPML_j$) are assumed to evolve as follows:

$$ML_{j,t} = (1 + g_j^{ML}) \times ML_{j,t-1} \,, \tag{23}$$

$$NPML_{j,t} = \left(1 - WRO_j - CurRate_j\right) \times NPML_{j,t-1} + PD_j \times PML_{j,t-1} \,, \tag{24}$$

$$PML_{j,t} = ML_{j,t} - PML_{j,t} \,, \tag{25}$$

where g_j^{ML} is the annual growth rate of mortgage loans (assumed equal to zero), WRO_j denotes the annual write-off rate (set to 20 percent), $CurRate_j$ denotes the cure rate (set to 15 percent), and the PD_j is the simulated PD from the micro module (eq. 19).

Provision stocks ($ProvStock_{j,t}$) and flows ($ProvFlows_{j,t}$) for non-performing mortgage loans evolve as:

$$(ProvStock)_{j,t} = LGD_j \times NPML_{j,t-1} \,, \tag{26}$$

$$(ProvFlows)_j = \Delta(ProvStock)_{j,t} + LGD_j \times WRO_j \times NPML_{j,t-1} \,, \tag{27}$$

where the LGD_j is the simulated LGD from the micro module (eq. 20).

The mortgage interest rate income $MII_{j,t}$ is defined as the product of performing mortgage volumes $PML_{j,t}$ with the corresponding mortgage interest rate IR_j (obtained from Table 3).[15] The interest income flows accounted for in eq. (22) reflect the interest that performing mortgages generate during the simulation.

The risk weighted assets for mortgages, $RWA_{j,t}$, are given by:

$$RWA_{j,t} = RW_j^{STA} \times PML_{j,t}^{STA} + RW_j^{IRB} \times PML_{j,t}^{IRB} + NPML_{j,t}^{STA,net} \,, \tag{28}$$

where *STA* and *IRB* denote the standardized and the internal ratings-based approaches for the measurement of the credit risk of banks, respectively.

The STA-based risk weight, RW_j^{STA}, is set to 35%, while the IRB-based risk weight, RW_j^{IRB}, is calculated according to the following *Basel* risk weight function:

$$RW_j^{IRB} = \left\{ LGD_j \times N\left[\frac{G(PD_j)}{\sqrt{(1-R)}} + \sqrt{\frac{R}{1-R}} \times G(0.999)\right] - PD_j \times LGD_j \right\}, \tag{29}$$

[15] We do not currently account for additional tax effects but plan to consider this in a future version of the model.

where $N(.)$ denotes the normal cumulative distribution function, $G(.)$ denotes the inverse cumulative distribution function, R is the correlation parameter (which is set to 0.15), and PD_j and LGD_j are the model outputs of the micro module following the policy implementation (eqs. 19 and 20).

The performing mortgage loan volumes for the IRB and STA portfolios are given by:

$$PML_{j,t}^{STA} = \left(1 - \left[\frac{IRB}{IRB+STA}\right]\right) \times PML_{j,t} \; , \tag{30}$$

$$PML_{j,t}^{IRB} = \left[\frac{IRB}{IRB+STA}\right] \times PML_{j,t} \; , \tag{31}$$

where the share of IRB mortgages in the total mortgage stock, $\left[\frac{IRB}{IRB+STA}\right]$, is obtained from Table 3.

The non-performing mortgage loan volumes, net of provisions, under the standardized approach, $NPML_{j,t}^{STA,net}$, are given by:

$$NPML_{j,t}^{STA,net} = \left(1 - \left[\frac{IRB}{IRB+STA}\right]\right) \times [NPML_{j,t} - (ProvStock)_{j,t}] \; , \tag{32}$$

D. Simulation Exercises

We start by obtaining the baseline country-specific PDs and LGDs. Having these as a benchmark, we can examine how the implementation of individual and joint policy limits of BBMs can improve the resilience of households and banks in a given country. We conduct three simulation exercises to this end:

D1) Effects of Borrower-Based Macroprudential Policy

We measure the short-term constraining effects of BBMs. For a given policy cap, we quantify the mortgage volume reductions due to BBMs. If a BBM cap is binding for a household, its loan amount is reduced to comply with the lending standard value at that cap.

D2) Resilience Benefits of Households and Banks from BBMs

We quantify the resilience benefits of households and banks after the imposition of policy caps. It is performed in two rounds:

First Round: For given BBMs (the policymaker's choice), the model computes the reduction in PDs, LGDs and LRs.

Second Round: The model translates the (scaled) negative loan demand shock resulting from the BBM cap from the first simulation into the impact on the macroeconomic variables. Using the impulse responses to an appropriately scaled shock to NFPS credit growth, the PDs and LGDs implied by the BBMs are recomputed a second time, to account for the macroeconomic feedback of the policy measures.

Then, the model computes the impact of the given BBMs on the capital adequacy ratio of banks (e.g., CET1, or total capital ratios), through the reduction in PDs and LGDs (including the second-round effects) of their mortgage portfolios. It also takes account of the impact through changing risk weights for the IRB portion of banks' mortgage portfolios.

D3) Analysis by Income and Wealth Groups

To evaluate the potentially heterogeneous impact of policies across these groups, we separate the population of borrowing households into those below the country income (wealth) median ("lower" income/wealth cohort) and those above ("higher" income/wealth cohort). We then conduct the previous two simulation exercises separately for each group.

4. Results and Policy Evaluation

For calibrating the BBMs, statistical distribution-informed thresholds were combined with information about the actual policy measures implemented in various countries (Table 7). The 75th percentile of the country-specific distribution of the respective lending standards in the HFCS data was taken as a starting point. Information on the actual calibrations implemented in practice was used to refine the calibrations. A calibration of this kind cannot reproduce the complexity of the BBM policy mix in individual countries, especially where multiple exemptions (speed limits), separate categories (e.g., distinguishing first time buyers and buy to let) or cross-lending standards limits are employed (see Jurča et al. 2020 for an example of the calibration details at the country-specific level).

4.1 The Impact of BBMs on the Resilience of Households

The cross-country distributions of country aggregated household risk parameters under "no policies" are compared with the respective post-policy distributions. Results are presented separately for four cases (Figure 4): the implementation of individual macroprudential limits to LTV, DSTI, DTI, and their joint application. For each of the four cases, we distinguish between the first and second-round effects. We also report the reduction in new mortgage lending flows in each of the four cases.

The application of BBMs improves PDs and LGDs notably, with the effect being more than additive when policy limits are applied jointly (Figure 4). The cross-country median loss rate decreases by about 0.15 pp when implementing the individual BBMs, with the effect almost doubling following the joint application of the policy measures (Table 8). With respect to the underlying credit risk parameters, the reduction in median PDs after accounting for the macroeconomic feedback is stronger (between 50-60 bps) as a result of applying income based BBMs (DSTI, DTI) compared with the 40 bps reduction as a result of the LTV limit. As was the case for the loss rate, this impact almost doubles to 100 bps when all three measures are applied jointly. This result would be consistent with income-based limits having a relatively stronger effect on household PDs. The impact on median LGDs is more diverse, with the effect of the DSTI limit being stronger (5 p.p. reduction) compared to that of LTV or DTI (2-3 p.p. reduction). Nevertheless, the joint impact of measures continues to be stronger (6 p.p. reduction).

Relative to the “no policy” benchmark, the reduction in new mortgage lending amounts to about -1 percent for the individual policies and more than -2 percent for the joint limits. The reduction in forgone new mortgage lending is computed as the percentage difference between the volume under no policies (the sum of all household-level mortgage amounts) and the policy-induced volume restriction for each individual policy and the joint limits, respectively. Figure 4(d) indicates that the policy-induced median reductions in the volume borrowed by households ranges between -0.8 and 1.5 percent across the cases where individual BBMs are applied.

The results suggest that the joint application of BBMs tends to have a stronger impact in terms of increasing borrower resilience when compared to individual limits. This can partly be attributed to the complementarities between the collateral-based measures acting primarily via the LGD channel and, respectively, income-based measures acting primarily via the PD channel. The effects are also conditional on the extent to which the policy limits on the individual and joint distribution of lending standards are binding, and in practice also on additional design elements of BBMs such as speed limits, limit differentiation by category, and other features. The macroeconomic environment, timing, and duration of BBM application also influence their effectiveness.

4.2 The Impact of BBMs on the Resilience of the Banking System

BBMs are found to have a notable effect on bank balance sheets, with median capital ratios of the banking systems in our sample increasing by up to 1 p.p. under the joint policy limits when compared to no-policies (Figure 5). The results are significant considering that the BBM transmission on balance sheets is modeled only via mortgage portfolios. Compared to the starting point for banking system balance sheets, the positive median impact on CET1 ratios ranges from 0.2 to 0.7 p.p. for the individual policy limits, with stronger effect for income-based limits (Table 9). The BBM impact on bank balance sheets can be decomposed into the positive effect of reducing the expected losses from mortgage loans alongside the lower RWAs (when PDs and LGDs drop) and the negative effect of foregone mortgage interest income given the new volume reduction resulting from the application of limits. Our results indicate a stronger contribution via the median reduction in RWAs (0.8 p.p.) compared with the reduction in expected losses (0.2 p.p.), when considering the application of joint BBMs and accounting for macroeconomic feedback effects.

In addition to significantly expanding the methodology, our results are consistent with the earlier results of GP (2017) which highlight the net benefits of BBMs in selected countries.

4.3 Comparing Policy Effects Across Income and Wealth Cohorts of Borrowing Households

The enhanced resilience of borrowing households is found to be stronger for the lower-income cohort (Figure 6). The impact of BBMs is presented relative to the no-policy benchmark as before, for the individual policy limit and accounting for second round macroeconomic effects. In terms of PD reduction, the policy effect for the households above the median income is negligible relative to the reduction for the lower-income households which ranges between -1 and -2 p.p. for individual policy limits and up to -3 p.p. when considering the joint limits (Figure 6(a)). To account for the potential heterogeneity across cohort starting points, we also compute the cohort-specific policy impacts *relative* to baseline PDs and LGDs (in addition to the *absolute* effects considered so far). The conclusions are the same in comparative terms[16]. The more sizeable resilience gain for the lower-income group is consistent with lower income borrowers being characterized by higher credit risk at origination. The median reduction in new mortgage lending for the group below the income median is also stronger, as the macroprudential limits are more binding for this group due to looser lending standards at origination (Figure 6(d)).

The analysis that splits households based on their net wealth suggests that the resilience of less wealthy borrowers is relatively more supported by BBMs, while new lending is compressed rather evenly among the two groups (Figure 7). The results suggest a stronger relative effect of BBMs for the lower-wealth group, albeit less pronounced than the differential measured based on income. Figure 7(b) shows that the PD reduction for lower-wealth groups ranges between -1 and -1.5 p.p. across the individual policy measures (approaching -2 p.p. when implementing measures jointly). Comparable results for the higher wealth group range between 0 and -1 p.p. across the individual and joint policies.[17]

[16] Taking the example of the impact under the joint policy caps, the cross-country median PD for the high-income cohort falls by 50% relative to the baseline, while that for the low-income cohort falls by 90%. The relative effect also holds for LGDs, although the difference is less pronounced (5.5% vs. 6.6%, respectively for high- and low-income cohorts).

[17] Our results differentiated by income and wealth cohorts represent an indicative starting point towards a distributional analysis of the effects of borrower-based measures on income and wealth inequality. They merely indicate a potentially heterogeneous impact of policies across income and wealth cohorts, without undertaking a comprehensive formal cost-benefit analysis which is left for future research. At the same time, we also note qualitatively the potential drivers of the results across income and wealth cohorts, related for example to the possible difference in risk characteristics and lending standards at origination, as the formal modeling at the cohort level is beyond the scope of this paper. Further, we will consider developing a means to assess the statistical significance of results for different wealth/income buckets, which is not as straightforward in the structural model here as it would be in an econometric model.

5. Conclusions

This paper sets forth an enhanced micro-macro model framework to assess the resilience benefits of implementing lending standard-related macroprudential policies for households and banks in the EU. We expand the IDHBS model of Gross and Población (2017) by introducing joint regulatory limits alongside an alternative way of measuring the loan volume effects of BBMs. The model was further enhanced by introducing an endogenous response of interest rates on deposits and loan to the short-term interest rates, distinguishing fixed and variable loan contracts, and employing a more advanced and realistic LGD module. Instead of the earlier multi-country GVAR model as its macro core, country-specific SVAR models were employed in this version.

Our analysis concludes that the resilience of households improves notably as a result of implementing individual and joint BBMs. The analysis looks at the resilience benefits of implementing BBMs (improvement in credit risk), while accounting for second round macroeconomic effects due to the credit-constraining impact of policy limits. The simulation results for a set of 19 EU countries suggest that LTV, DSTI and DTI caps can help reduce PDs, LGDs and hence loss rates for the household sector. The joint implementation of measures produces effects which are "more than additive," that is, their impact exceeds the sum of the effects of the underlying individual caps.

We find a positive impact of BBMs on the capital ratios of banking systems, compared to the "no policy" benchmark scenario. The policy impact transmits via the improvement in the credit risk parameters attached to mortgage portfolios, the associated changes in expected losses, and risk weights. The positive impact on bank capitalization is quantitatively notable, despite the partial policy transmission to bank balance sheets only via the banks' retail mortgage portfolios.

Finally, the analysis distinguishes the resilience benefits across income and wealth categories and finds that policies are more effective across lower income/wealth borrowers. The policy-induced reduction in PDs for borrowers with income or wealth below the median is stronger, compared to higher income/wealthier borrowers. This effect should be seen in conjunction with the below median income/wealth households' risk parameters also being generally more elevated at origination compared to higher income/wealth households. Against this combined analytical finding, otherwise borrower characteristic-independent BBMs can be expected to help contain the credit risk of households in the lower income and wealth portion of the population more strongly.

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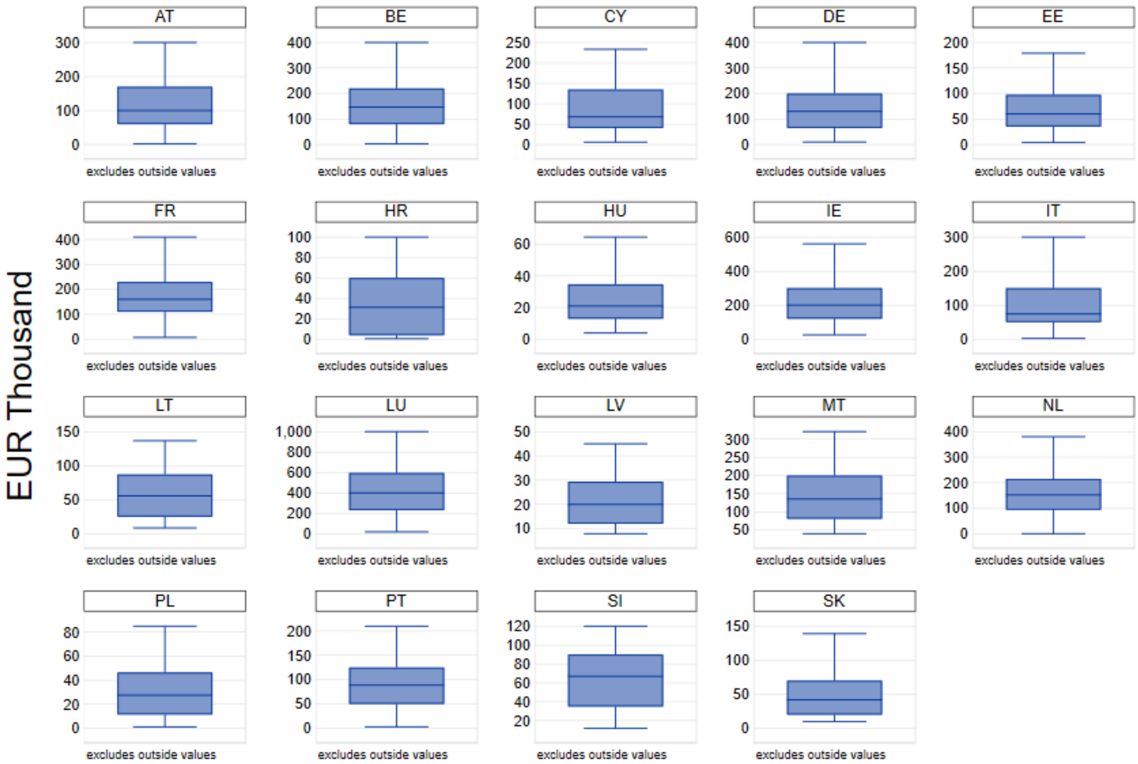
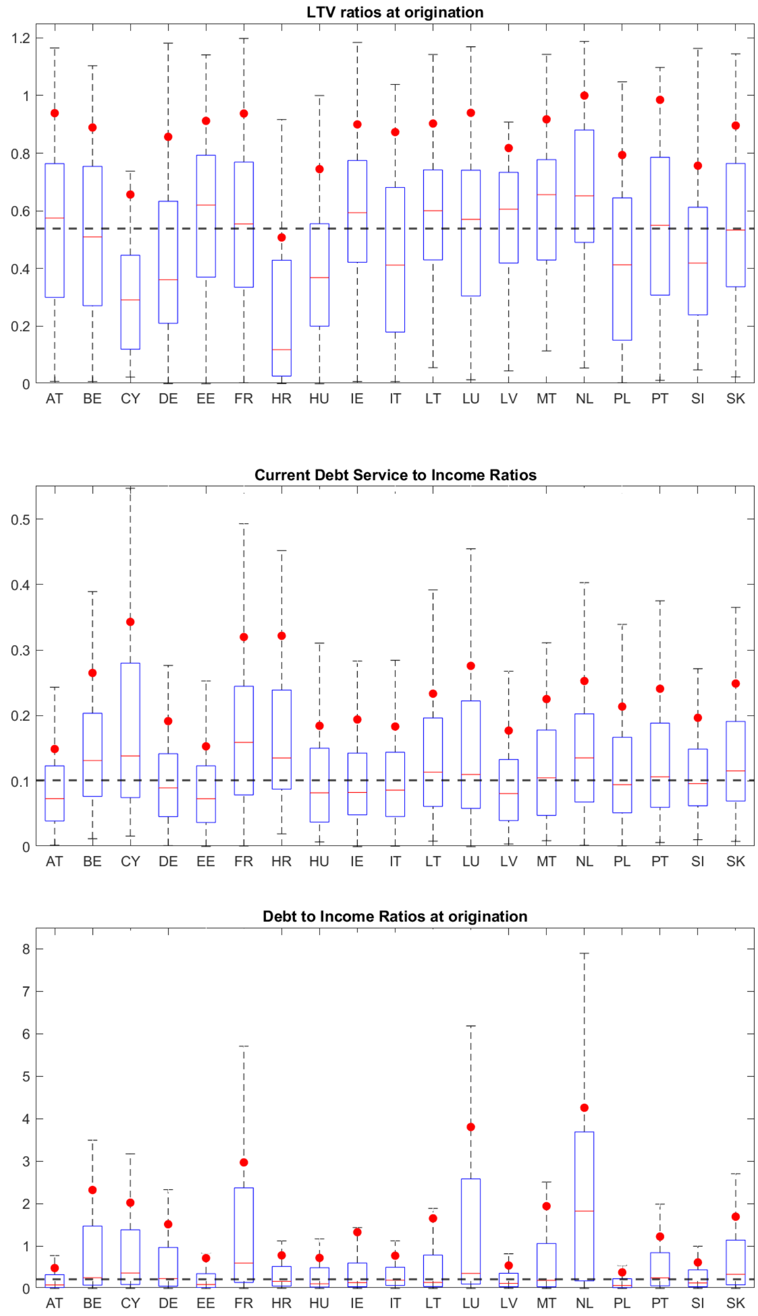
Figures and Tables

Figure 1: Country-Specific Distributions of HFCS Mortgage Volumes at Origination (2014-2017)



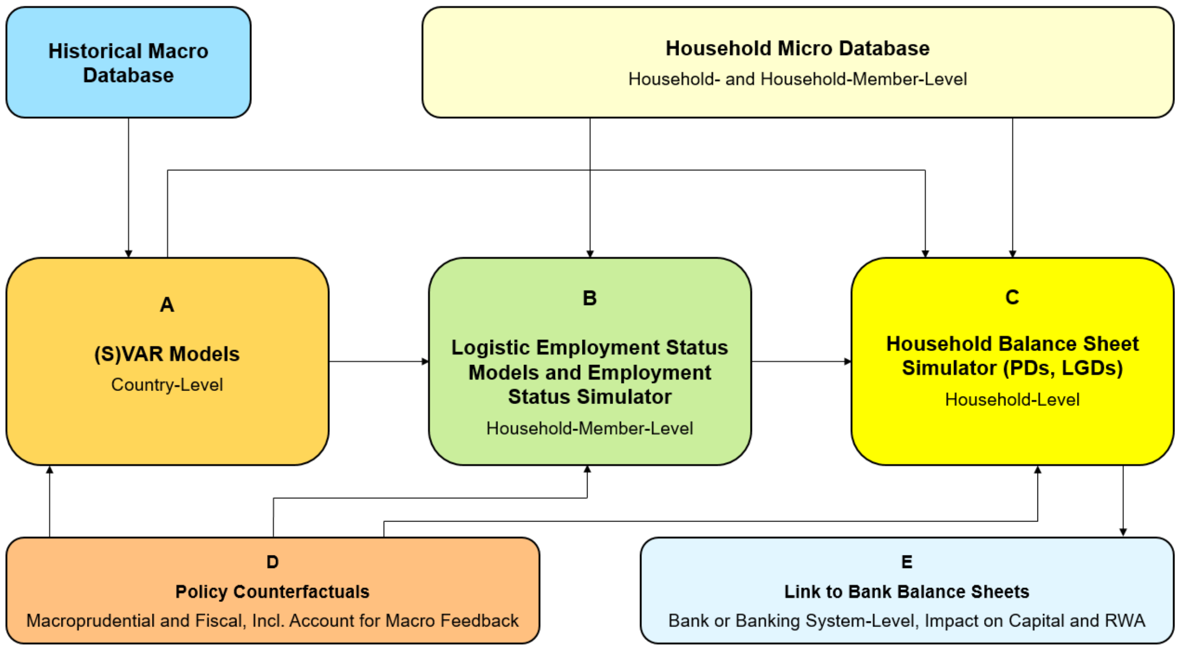
Notes: This figure presents the country-specific distributions of mortgage volumes (in thousand euro) at origination over the period 2014-2017. Outliers have been excluded. Data comes from the 3rd wave of the Household Finance and Consumption Survey (HFCS).

Figure 2: Country-Specific Distributions of Lending Standard Indicators

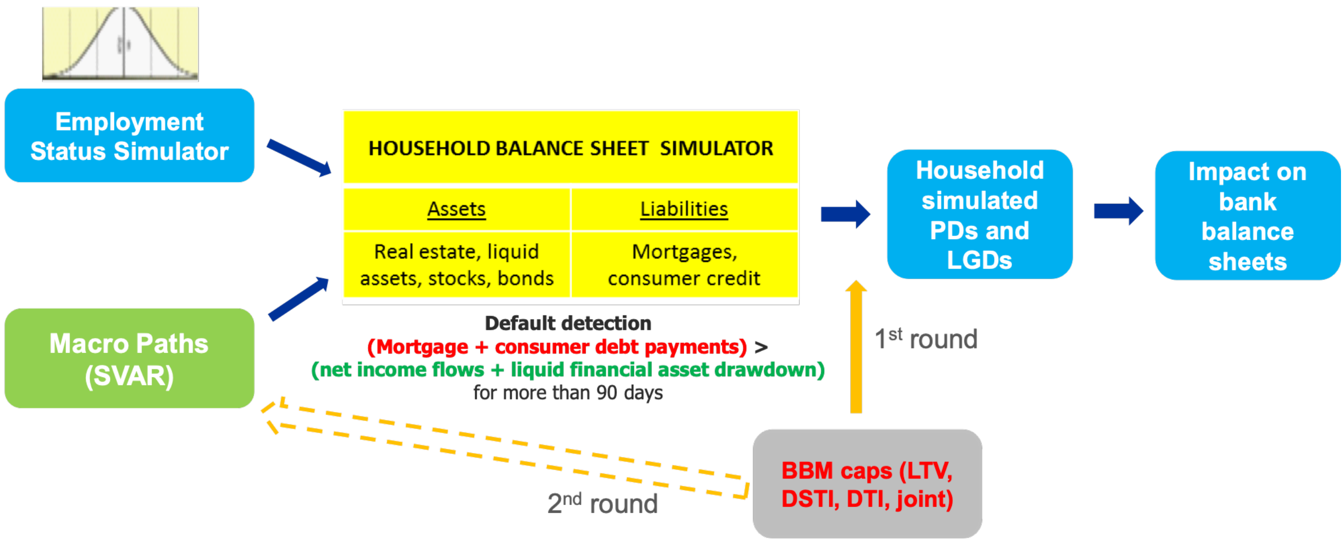


Notes: This figure presents the country-specific distributions of the LTV (at loan origination), current debt-service-to-income and debt-to-income ratios over the period 2014-2017. Red dots mark to the 90th percentile of the distributions. The dotted horizontal line is the cross-country sample median. Whiskers extend to the maximum and minimum value after outliers have been excluded. Data comes from the 3rd wave of the Household Finance and Consumption Survey (HFCS).

Figure 3: Structure of the Modeling Framework



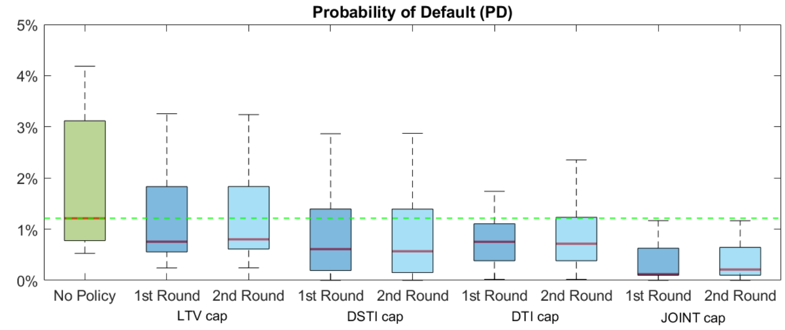
Panel (a): Conceptual Overview



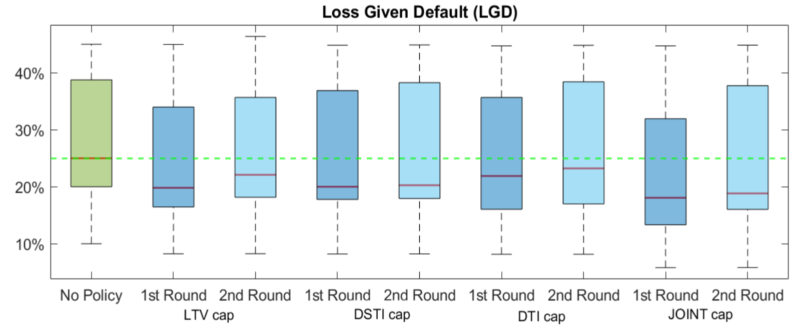
Panel (b): Technical Overview

Figure 4: Impact of Borrower-Based Measures on Household Risk Parameters

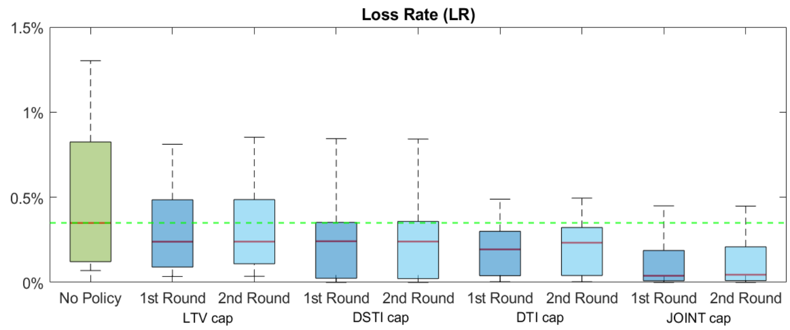
Panel (a)



Panel (b)



Panel (c)



Panel (d)

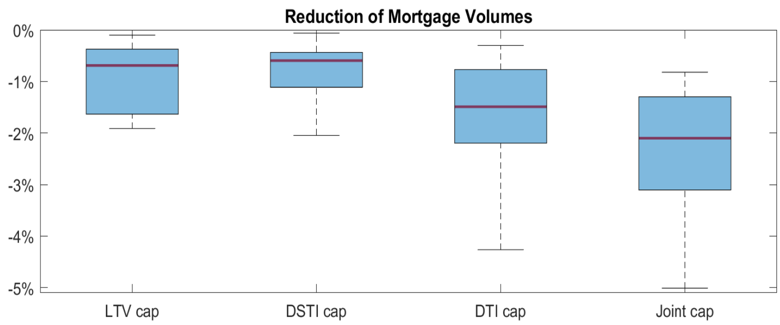
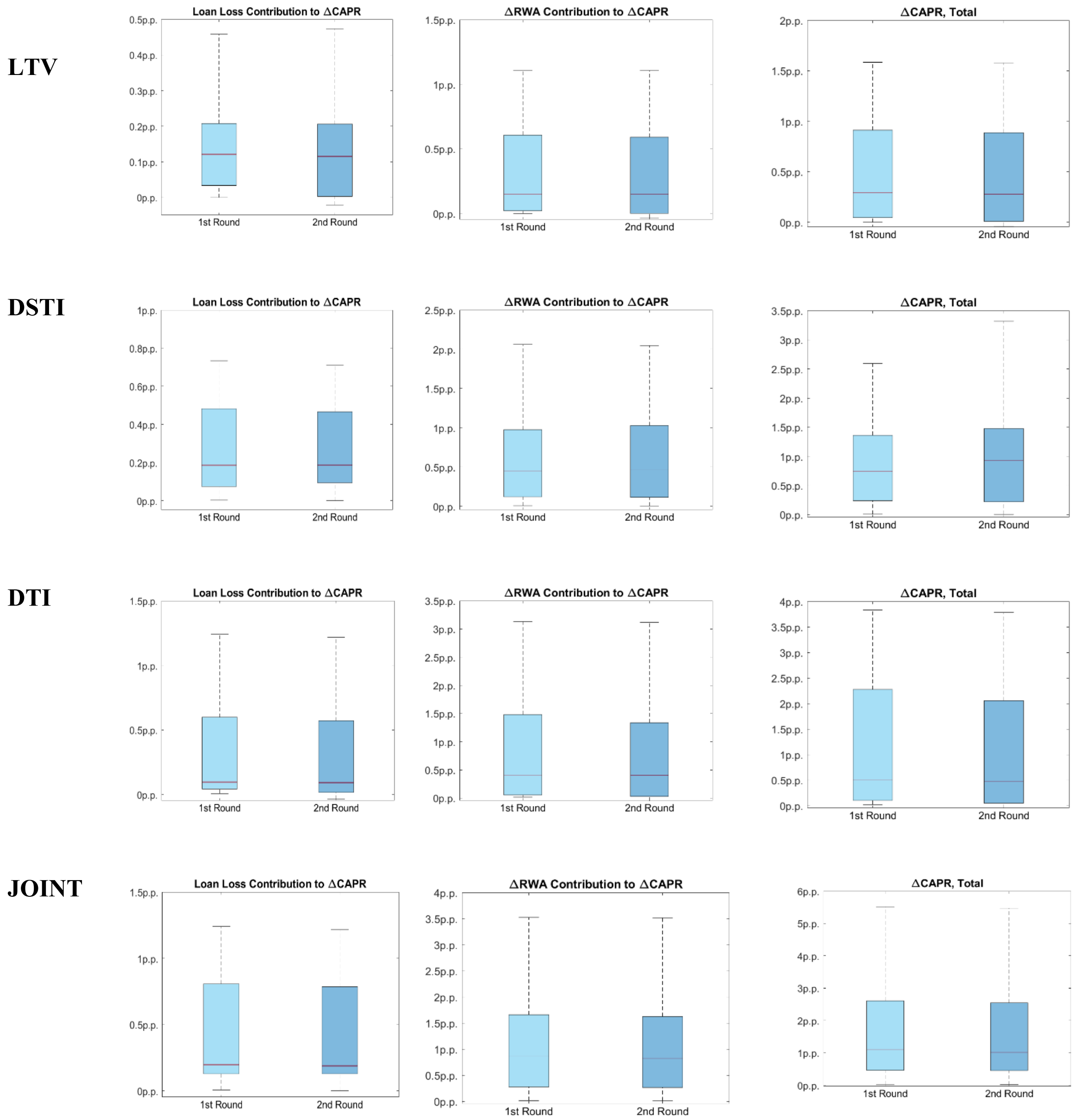


Figure 5: Impact of Borrower-Based Measures on Banks' Solvency Positions



Notes: In **Figure 4,** the box plots in panels a)-c) reflect the median and 25th-75th percentiles across households 'PDs, LGDs, LRs and mortgage volumes reductions aggregated at the country level across countries. The green bar and the respective median line refer to the PDs (LGDs or LRs) without borrower-based measures in place (no policies), the dark blue bars and median lines refer to the 1st round impact of the policy tightening in terms of enhanced resilience (reduction in PDs, LGDs, LRs), separately for each policy instrument (LTV, DSTI, DTI) and for their joint application. The light blue bars and median lines reflect the effects after taking 2nd round macroeconomic effects from the policy induced negative credit demand shock into account. Panel d) shows the median and 25^{th}-75^{th} percentiles of the reduction in new mortgage lending under the policy instruments.

Figure 5 reflects the median and 25th-75th percentile distribution of changes in bank capital ratios across the banking systems in our sample resulting from the implementation of borrower-based measures. The impacts result from a combination of a reduction in loan losses and risk weights, due to improved credit quality of the banks' mortgage portfolios (via lower PDs and LGDs). The light blue bar and median line refer to the 1st round impact under the joint policy caps (LTV and DSTI and DTI). The dark blue bar and median line depict the impacts after 2nd round macroeconomic effects implied by the negative credit demand shock are accounted for. Whiskers extend to the maximum and minimum value.

Figure 6: Impact of Borrower-Based Measures Across Income Cohorts

Panel (a)

Panel (b)

Panel (c)

Panel (d)

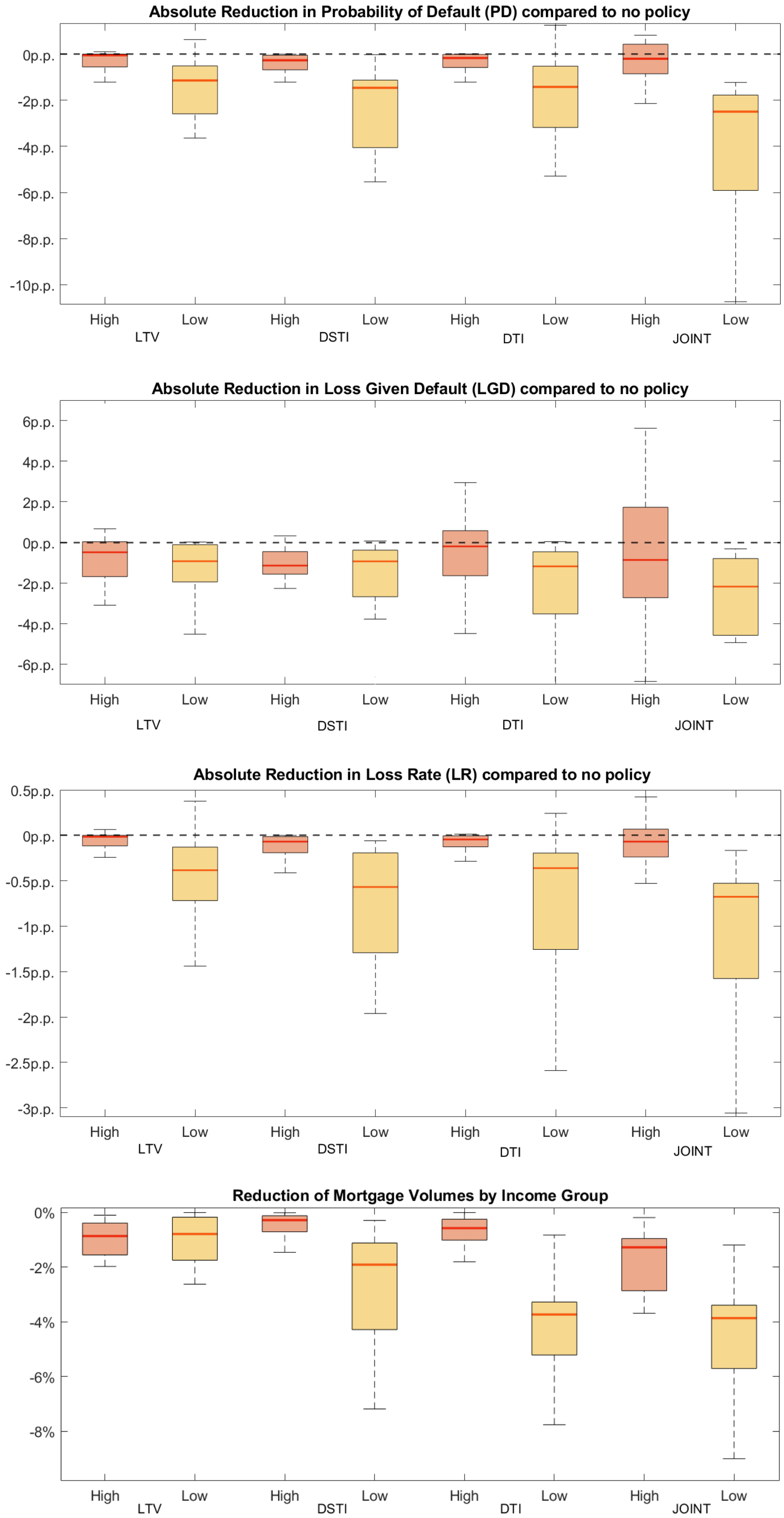
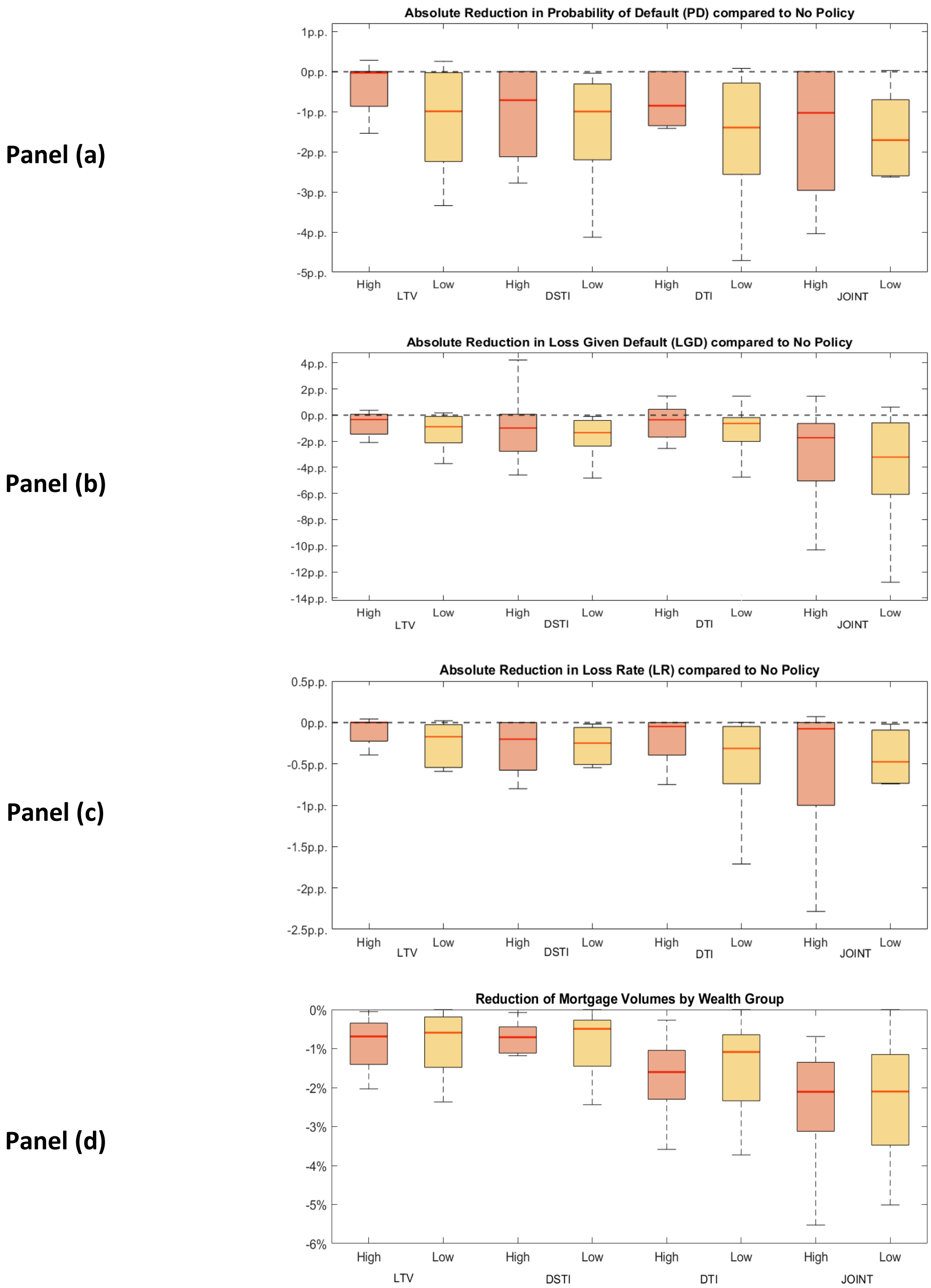


Figure 7: Impact of Borrower-Based Measures Across Wealth Cohorts



Notes: These figures present the absolute reductions in PDs, LGDs, LRs and mortgage volumes due to the implementation of lending standard-related macroprudential policies for low (yellow bars) and high (orange bars) income (figure 6) and, respectively, wealth (figure 7) borrowers. The bars and median lines refer to the impact of the policy tightening in terms of enhanced resilience (reduction in PDs, LGDs and LRs), separately for each policy instrument (LTV, DSTI, DTI) and for their joint application, accounting for 2nd round macroeconomic effects from the policy-induced negative credit demand shock. Whiskers extend to the maximum and minimum value.

Table 1: HFCS Variables and their Mapping into the Model

		Model Variable		Variable Code in the HFCS + Transformation
HH-Level	Assets	H	Current value of house	DA1110
		TFA	Total financial assets (incl. cash, stocks, bonds, pensions, life insurance)	DA2100 - DA2104 (value of business) - DA2107 (money owed to others)
		B	Current market value of bonds	DA2103
		S	Current market value of stocks	DA2105
	Liabilities	D^M	Outstanding balance of mortgage debt	DL1100
		D^{NM}	Outstanding balance of non-mortgage debt	DL1200
	Income Flows	I	Household income total, quarterly, gross of tax (used only for calculation of DSTI and DTI ratios for MPRU policy exp.; labor income, pensions, and unemployment benefit are used and modeled at HH member-level)	DI2000 / 4
		RI	Rental income, quarterly	HG0310 / 4
		OI	Other regular income, quarterly, e.g. child benefit, alimony, etc.	(HG0110 + HG0210) / 4
	Expense Flows	$A = A^M + A^{NM}$	Annuity for mortgage debt, quarterly	DL2100 * 3
			Annuity for non-mortgage debt, quarterly	DL2200 * 3
		OE	Rental expense, quarterly (needed only if focus is on HHs who rent)	HB2300 * 3
		E	Living expense, excl. annuities and rent, quarterly	DOCOGOOD / 4
	Other	HH_ID	Household ID	SA0010 (made unique across countries)
		HW	Household weight	HW0010
		HH_RES	Country of residence	SA0100
		Myear	Year of 1st mortgage origination; for MPRU exp. only	HB1301
		MiniDur	Duration of 1st mortgage at origination in years; for MPRU exp. only	HB1601
		DType	Rate type of total debt (variable vs. fixed)	DL1110{a,b,c}i
		i^M	Current interest rate on mortgage debt; if not reported at HH-level, then filled with country-aggregate consumer debt interest rate	W.A. from mortages outstanding (HB170x) and their interest rates (HB190x)
		i^D	Current interest rate on total debt; if not reported at HH-level, then filled with country-aggregate consumer debt interest rate	Total absolute annual interest flow (DI1412) over total current debt (DL1000)
		M^{RES}	Synthetic residual duration of total debt in months (needed for variable rate loans only)	ceil(log(4*A./(4*A-i^D.*(D^M+D^{NM}))).log((i^D./12)+1))
		EtoI	Living expenses (excl. Annuities and rent) as share of gross income	E/I
HM-Level	Income Flows	INC^E	Labor income (gross of tax) from employment or self-employment, public/private pension income (net of tax), quarterly	(PG0110 + PG 0210 + PG0310 + PG0410) / 4
		INC^U	Unemployment benefit, net of tax, quarterly	PG0510 / 4
	Other	HM_ID	Household member ID	ID
		HM_HH_map	Household members' household IDs	SA0010
		HM_RES	Country of residence	SA0100
		LAB	Labor status; see separate table for code mapping	PE0100a
		MAR	Marital status; see separate table for code mapping	PA0100
		EDU	Level of education; see separate table for code mapping	PA0200
		GEN	Gender	RA0200
		AGE	Age	RA0300
		DF	Nationality / Domestic-foreign indicator	Generated from country of birth

Notes: The table summarizes how the variables contained in the HFCS are mapped into the model.

Table 2: Definitions for the Lending Standard Indicators Subject to Borrower-Based Macroprudential Limits

Variable	Formula	Details
iLTV	$iLTV = \frac{iL}{iV} = \frac{MortageDebtatOrigination}{PropertyValueatTimeofAcquisition}$	iL = HB1401 from HFCS data iV = HB0800 from HFCS data
cDSTI	$cDSTI = \frac{cATD}{cAGI} = \frac{AnnualizedTotalDebtService}{AnnualGrossIncome}$ $cADT = \begin{array}{c}(annualizedannuityflowformortgagedebt)\\+\\(annualizedannuityflowforotherdebt)\end{array}$	$cAGI$ = DI2000 from HFCS data $cADT$ =12*DL2100 + 12*DL2200 DL2100, DL2200 from HFCS data
iDTI	$iDTI = \frac{iTOD}{cAGI} = \frac{OutstandingBalanceofTotalDebt}{AnnualGrossIncome}$ $iTOD = iL + (outstandingbalanceofotherdebt)$	$outstandingbalanceofotherdebt$ =DL 1200 from HFCS data

Notes: iLTV denotes the loan-to-value ratio at loan origination, cDSTI denotes the current debt-service-to-income ratio, iDTI combines the stock of mortgage debt at origination with the current stock of non-mortgage debt. For simulation purposes the upper limits of the 3 ratios are capped at 1.2, 1.2 and 30 respectively.

Table 3: Banking Module Parameters

Input Parameters	Explanation	Source
RWA Total	Risk Weighted Assets	ECB Statistical Data Warehouse
CET1 Total	Core Equity Tier 1 Capital	ECB Statistical Data Warehouse
IRB/(IRB+STA)	Share of IRB mortgages in total mortgage stock	EBA
RW on STA mortgage portfolio	Implied by regulation	BCBS
Mortgage loan stock - performing	Performing mortgage loans	ECB Statistical Data Warehouse
Mortgage loan stock - nonperforming	Non-performing mortgage loans	ECB Statistical Data Warehouse
PiT PD	Mortgage PD anchor point for the last sample year (2017)	EBA Risk Dashboard
PiT LGD	Mortgage LGD anchor point for the last sample year (2017)	EBA Risk Dashboard
TTC PD of mortgages	Through the cycle PD - estimated PD for the upturn of the cycle	EBA
DT LGD of mortgages	Downturn PD - estimated for the downturn of the cycle	EBA
Mortgage loan interest rates		ECB Statistical Data Warehouse
Pass-through parameter	Pass-through rate from point in time PDs and LGDs to respective regulatory credit risk parameters	

Table 4: Calibration of Banking Module Parameters

Parameter calibration	AT	BE	CY	DE	EE	FR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK
RWA Total (bn EUR)	360.3	159.7	31.6	2482.1	10.5	2422.3	2.8	38.0	215.5	1097.4	11.6	41.7	7.9	9.7	706.1	259.7	154.5	13.6	34.0
CET1 Total (bn EUR)	54.8	25.6	4.5	393.3	0.7	333.2	0.5	4.9	49.3	149.2	2.2	11.2	1.3	1.6	117.3	23.5	21.4	4.3	1.4
Mortgage IRB/(IRB+STA) (share)	0.9	1.0	0.3	1.0	1.0	0.9	0.2	0.4	0.8	0.9	0.8	0.7	0.6	0.3	1.0	0.2	0.5	0.3	1.0
RW on STA mortgages (percent)	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Mortgage loan stock – performing (bn EUR)	88.5	134.9	6.1	742.0	1.3	524.9	0.4	104.8	84.2	319.1	0.0	21.4	0.8	2.7	730.2	42.1	67.0	2.0	2.8
Mortgage loan stock – nonperforming (bn EUR)	3.4	4.6	6.5	14.4	0.0	19.8	0.0	12.0	14.2	33.7	0.0	0.5	0.1	0.1	8.6	3.3	5.9	0.1	0.1
PiT PD (percent)	1.2	1.1	1.3	0.7	0.5	1.0	1.4	3.3	4.0	3.9	1.7	0.7	2.7	0.6	0.7	1.1	3.3	4.2	0.9
PiT LGD (percent)	20.0	10.0	20.0	15.0	25.0	25.0	40.0	40.0	20.0	30.0	35.0	10.0	45.0	20.0	10.0	40.0	25.0	20.0	40.0
TTC PD of mortgages (percent)	1.4	1.4	1.3	0.9	1.4	1.2	1.4	3.3	3.6	1.8	1.7	1.1	2.7	0.6	0.6	1.1	6.0	4.2	1.3
DT LGD of mortgages (percent)	13.5	14.6	17.7	18.0	12.9	13.5	29.3	33.3	23.4	19.7	16.6	13.1	18.1	26.6	16.9	30.0	21.7	18.0	20.4
Mortgage loan interest rates (percent)	1.9	2.3	3.1	2.8	1.7	2.3	2.0	4.7	2.6	2.2	1.6	1.9	2.3	3.1	3.4	3.7	1.1	2.3	2.4
Pass-through parameter (percent)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 5: Micro and Macro Module Parameters

Variable	Comments	Source
URX	Unemployment rate anchor point for the last year (2017)	ECB Statistical Data Warehouse
IR	Short-term interest rate level anchor point for the last year	ECB Statistical Data Warehouse
HPG	Annual house price growth in the last year (log difference-based)	ECB Statistical Data Warehouse
SPG	Annual stock price growth in the last year (log difference-based)	ECB Statistical Data Warehouse
CPG	Annual compensation per employee growth in last year (log difference-based)	ECB Statistical Data Warehouse
DEPR	Deposit rate in the last sample year	ECB MIR
DUR	Average duration of unemployment in quarters	OECD
COSTL_E	Consumption expenditure rate, for employed household members (HM population median)	HFCS
COSTL_U	Consumption expenditure rate, for unemployed household members (HM population median)	HFCS
INCTAX	Income tax	OECD
URXTAX	Tax on unemployment benefit	-
REPRATE	Net of tax unemployment benefit over previous income gross of tax (hence tax rate for URX benefit should be set to zero)	OECD
PD	Mortgage PD anchor point for the last sample year	EBA Risk Dashboard
LGD	Mortgage LGD anchor point for the last sample year	EBA Risk Dashboard
CURERATE	Cure rate	-
g	Ratio of total household new business flows during the whole sample period to total NFPS lending stock as at end of the last sample year (divided by 12 to obtain a quarterly measure)	ECB BSI
MaxURXBEN	Ceiling on monthly gross unemployment benefit flow in local currency	EC
Recourse	Recourse indicator. 1 = Full recourse, 2 = no or limited recourse	-
DEP_alpha_down	Persistence parameter of deposit rates (1-pass through strength from base rate) when base rates move down	ECB BSI and own estimates
DEP_alpha_up	Persistence parameter of deposit rates (1-pass through strength from base rate) when base rates move up	ECB BSI and own estimates
IREG	Interest type regime 1 = adjustable-rate mortgages predominant, 2 = fixed rate mortgages predominant	-

Table 6: Calibration of Micro-Macro Module Parameters

Parameter	AT	BE	CY	DE	EE	FR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK
Unemployment Rate (percent)	5.5	7.1	11.1	3.8	5.8	9.4	11.	4.2	6.7	11.	7.1	5.6	8.7	4.0	4.9	4.9	9.0	6.6	8.1
Long-term interest rate (percent)	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	0.6	0.2	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	1.7	-0.3	-0.3	-0.3
House prices growth (percent)	4.5	3.6	1.8	6.3	4.8	3.2	7.4	12.1	11.2	-1.2	6.6	4.0	7.6	9.0	7.9	3.8	10.1	9.5	5.7
Stock prices growth (percent)	29.2	13.1	8.7	19.0	16.7	16.0	-6.5	25.9	11.1	26.7	16.8	4.6	33.8	0.5	17.2	30.8	16.4	9.8	2.3
Growth in compensation per employee (percent)	1.9	2.7	0.8	2.7	7.6	2.0	-0.2	6.9	3.1	1.0	9.2	2.3	6.4	1.9	1.5	7.1	2.7	3.9	5.4
Deposit Rate (percent)	0.5	1.5	1.5	0.9	0.6	2.0	0.8	0.7	0.4	1.1	0.4	0.5	1.1	1.3	2.3	0.5	0.5	0.5	0.9
Unemployment Duration (unit?)	2.69	2.69	5.08	2.69	5.08	2.69	5.08	5.87	2.69	2.69	5.08	2.69	5.08	5.08	2.69	3.93	2.69	5.08	5.28
Consumption Expenditures Rate, Employed (percent)	31	34	44	21	43	27	80	51	33	54	69	29	50	40	13	59	48	53	61
Consumption Expenditures Rate, Unemployed (percent)	31	34	44	21	43	27	80	51	33	54	69	29	50	40	13	59	48	53	61
Income Tax (percent)	29.4	32.9	25.0	29.9	13.7	22.5	25.0	28.1	20.3	28.3	36.1	23.0	24.4	25.0	27.8	22.4	21.6	25.0	19.3
Tax on Unemployment Benefit (percent)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Unemployment Benefit, net of tax (percent)	36.7	37.2	30.5	29.7	28.3	45.2	22.8	10.0	35.9	23.6	18.2	45.2	25.6	32.1	47.0	22.2	44.6	29.6	19.5
Mortgage PD, EBA anchor (percent)	1.21	1.14	1.27	0.74	0.53	1.02	1.42	3.26	3.97	3.87	1.67	0.71	2.70	0.59	0.69	1.09	3.34	4.18	0.87

Mortgage LGD, EBA anchor (percent)	20	10	20	15	25	25	40	40	20	30	35	10	45	20	10	40	25	20	40
Cure rate (percent)	5	5	10	10	5	5	5	5	5	5	5	5	5	5	25	5	5	5	5
HH New Business Flow, percent of NFPS	19.9	45.3	5	31.5	24.8	24.0	27.4	27.4	13.8	19.5	23.2	27.4	17.6	27.4	14.9	61.4	14.1	33.4	55.7
Celling for monthly unemployment benefit (EUR)	1250	1800	1000	1500	400	3500	300	150	1500	1200	800	2250	500	400	2800	500	800	350	350
Recourse Indicator (1= recourse active)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Persistence parameter of deposit rates (base rates move down)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Persistence parameter of deposit rates (base rates move up)	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Interest Type Regime (1=, 2=)	1	2	1	2	1	2	1	2	1	2	1	1	1	1	1	1	1	1	1

Table 7: Calibration of Borrower-Based Macroprudential Limits

Country	iLTV	cDSTI	iDTI
Austria	80%	28%	4.0
Belgium	90%	34%	6.0
Cyprus	90%	40%	4.0
Germany	90%	40%	4.0
Estonia	85%	43%	4.0
France	90%	26%	4.0
Croatia	90%	40%	4.0
Hungary	90%	40%	4.0
Ireland	90%	40%	3.5
Italy	90%	40%	4.0
Lithuania	85%	32%	4.0
Luxembourg	85%	42%	6.2
Latvia	90%	30%	4.5
Malta	90%	30%	4.0
Netherlands	100%	22%	4.0
Poland	90%	40%	4.0
Portugal	90%	39%	4.0
Slovenia	80%	38%	4.0
Slovakia	80%	48%	6.5

Notes: The three BBMs are: the loan-to-value ratio at the loan origination (iLTV); the current debt-service-to-income ratio (cDSTI); and the income-to-debt ratio at the loan origination (iDTI). Starting from the 75th percentile of the country-specific lending standards distributions in the HFCS data, the calibrations are further aligned to approximate the actual calibrations in place across countries. The calibrations do not include more complex design features of the policy measures such as speed limits or differentiation across borrower categories (e.g., first time borrowers, buy to let, etc.).

Table 8: Impact of Borrower-Based Measures on Household Resilience Parameters

Median over 19 EU countries		Policy cap			
		LTV	DSTI	DTI	Joint
PD	No Policy	1.21%			
	1st round	0.76%	0.61%	0.75%	0.12%
	2nd round	0.80%	0.57%	0.72%	0.21%
LGD	No Policy	25.00%			
	1st round	19.81%	20.00%	21.89%	18.05%
	2nd round	22.09%	20.25%	23.21%	18.83%
LR	No Policy	0.35%			
	1st round	0.24%	0.24%	0.19%	0.04%
	2nd round	0.24%	0.24%	0.23%	0.04%

Notes: Cross-country median levels of PDs, LGDs and LRs under no policies and, respectively, after the 1st and 2nd round impact of borrower-based measures.

Table 9: Impact of Borrower-Based Measures on the Capital Position of Banking Systems

Median over 19 EU countries, deviation from no policy		Policy Cap			
		LTV	DSTI	DTI	Joint
Loan Loss Contr. to ΔCAPR	1st round	0.12pp	0.19pp	0.10pp	0.20pp
	2nd round	0.12pp	0.19pp	0.09pp	0.19pp
ΔRWA Contr. to ΔCAPR	1st round	0.15pp	0.45pp	0.41pp	0.87pp
	2nd round	0.15pp	0.46pp	0.40pp	0.82pp
ΔCAPR	1st round	0.29pp	0.74pp	0.50pp	1.10pp
	2nd round	0.28pp	0.93pp	0.48pp	1.01pp

Notes: Median increase (relative to no-policies) in solvency ratios across the banking systems in the sample resulting from the reduced loan losses and decreased risk weights associated with the increased credit quality of mortgage portfolios.

Appendix A: Estimation Results from Logistic Models for the Employment Status

Table A1 reports the estimation results for the country-specific logistic models described in Section 3.3/B2.

Table A1: Logistic Model Estimates for Employment Status

Coefficients	AT	BE	CY	DE	EE	FR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK
Constant	4.395	2.302	2.494	3.820	2.200	1.263	0.920	4.061	3.488	0.850	4.048	2.280	3.370	5.403	4.353	2.835	2.731	3.525	2.503
Marital Status	-1.135	-1.212	-1.295	-1.114	-0.248	-0.867	-0.579	-0.718	-1.031	-0.696	-0.681	-0.308	-0.702	-0.756	-0.219	-0.827	-0.767	-0.955	-0.686
Education Level	-1.138	-0.851	-0.931	-1.151	-0.794	-0.847	-0.917	-1.127	-0.900	-0.941	-0.809	-0.836	-1.051	-2.317	-0.998	-1.300	-0.947	-0.977	-1.691
Gender	-0.168	-0.035	0.489	-0.124	-0.197	0.160	0.572	0.044	-0.119	-0.017	-0.367	0.062	-0.520	0.536	0.520	0.627	0.160	0.510	0.079
Nationality	0.818	0.708	0.366	1.081	0.757	0.807	0.422	-0.607	0.091	-0.243	0.066	0.953	0.081	-0.282	0.474	0.393	0.032	0.118	0.646
Age	-0.022	0.009	-0.005	-0.008	0.015	0.027	0.008	0.010	0.000	0.045	-0.019	0.030	0.013	0.000	-0.035	-0.001	0.003	-0.021	0.008
P-Value																			
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Marital Status	0.000	0.000	0.000	0.000	0.139	0.000	0.000	0.000	0.000	0.000	0.000	0.211	0.003	0.010	0.212	0.000	0.000	0.000	0.000
Education Level	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Gender	0.218	0.810	0.000	0.351	0.185	0.004	0.000	0.683	0.246	0.790	0.032	0.788	0.025	0.066	0.001	0.000	0.025	0.000	0.519
Nationality	0.000	0.000	0.052	0.000	0.001	0.000	0.046	0.187	0.472	0.025	0.773	0.000	0.831	0.703	0.011	0.481	0.795	0.686	0.225
Age	0.000	0.161	0.353	0.139	0.027	0.000	0.150	0.026	0.000	0.000	0.007	0.008	0.165	0.000	0.000	0.774	0.418	0.000	0.136
Statistics																			
Observations	3325	2194	2101	5300	3497	15308	1645	6380	5728	6750	1869	2104	1507	1104	2343	6878	7319	2568	2403
AUROC	0.670	0.694	0.668	0.715	0.641	0.697	0.598	0.668	0.673	0.677	0.645	0.697	0.695	0.704	0.680	0.670	0.623	0.654	0.659
Gini	0.368	0.436	0.395	0.451	0.299	0.437	0.273	0.356	0.376	0.451	0.317	0.409	0.417	0.427	0.388	0.380	0.283	0.354	0.371

Notes: This Table presents the logistic model estimates for the employment status of individual household members contained in the HFCS (19 EU countries). The left-hand side variable is coded as 0 = unemployed, 1 = employed. Marital status: 0 = married, 1 = single. Education: 0 = university degree, 1 = no university degree. Gender: 0 = female, 1 = male. Nationality: 0 = foreign, 1 = domestic national.

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