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Assessing the efficacy of borrower-based macroprudential policy using an integrated micro-macro model for European households

HFCS

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Abstract

We develop an integrated micro-macro model framework that is based on household survey data for a subset of the EU countries that the Household Finance and Consumption Survey (HFCS) contains. The model can be used for conducting scenario and sensitivity analyses with regard to the factors that drive households' income and expenses as well as their asset values and hence the structure of their balance sheet. Moreover, we use it for the purpose of assessing the efficacy of borrower-based macroprudential instruments, namely loan-to-value (LTV) ratio and debt service to income (DSTI) ratio caps. The simulation results from the model can be attached to bank balance sheets and their risk parameters to derive the impact of the policy measures on their capital position. The model framework also allows quantifying the macroeconomic feedback effects that would result from the policy-induced reduction of demand for mortgage loans. The model allows answering the question as to which of the two measures — LTV or DSTI caps — are more effective, both with respect to their ability to reduce household loss rates as well as their impact on the economy.

Keywords: Household balance sheets, macro-financial linkages, stress-testing, macroprudential policy

JEL classification: C33, E58, G18

Non-technical summary

We develop an integrated dynamic balance sheet model for the household segment from 15 European countries; those comprised by the Eurosystem Household Finance and Consumption Survey (HFCS). We refer to the framework as the Integrated Dynamic Household Balance Sheet (IDHBS) model. The model can be used for two purposes.

First, the model can be used to conduct stress tests based on some baseline and hypothetical adverse macro-financial scenarios, both from the perspective of the household sector itself, by assessing how default rates and loss given default parameters for the households would evolve under the scenarios as well as the perspective of banks to whose balance sheets we can attach the simulated household parameters to assess the banks' ability to withstand stress in the household sector across countries.

Second, the aim is to use the model to assess how lending standard-related macroprudential policy instruments would affect households. The imposition of loan-to-value (LTV) ratio or debt service to income (DSTI) caps for instance will be assessed, under either an unconstrained scenario or one under which LTV or DSTI ratio caps are imposed. The households' risk parameter responses can be assessed with a view again to both the households themselves and also the subsequent impact on bank balance sheets. The focus of this paper is in fact this latter application of the model for an assessment of borrower-based macroprudential policy.

The model has two core components: first, a *macro component* which uses the Global Vector Autoregressive (GVAR) model structure to capture the dependencies of variables that drive the size and structure of household balance sheets: house prices, short- and long-term interest rates (related to the income that households receive from their deposits and bond holdings for instance, but also their expense when paying down their debt), and stock prices (related to financial stock holdings). Alongside the asset prices, the macro module also contains aggregate, country-level unemployment rates which are an important input for the micro part of the model. The macro part is integrated with a *micro component* of the IDHBS model which has a household member-level logistic model for the employment status at its heart. Technically integrating these two components is important as the dependency between the evolution of income, asset prices and employment rates over the business cycle need to be captured properly. The integrated model can then be used to conduct stochastic forward simulations, either in an unconditional manner or conditional on predefined macro-financial scenarios and with or without policy caps.

The model and the impact assessment that can be conducted with it is meant to shape our understanding of how lending standard-related macroprudential instruments exert their impact on the economy. LTV caps shall exert their impact primarily through reducing loss given default parameters for the lender because the ratio is directly related to the value of the underlying collateral. DSTI caps on the other hand should exert their impact primarily through a reduction in the probability of households to default on their debt, i.e. it is related to their PD. The results from the model clearly confirm this. They, however, also suggest that the model-implied PDs and LGDs for households correlate such that both policies affect also the respective other risk parameter. This is not a necessity in countries of which many in Europe are known to give little rise to incentives for strategic default; unlike in the US where that incentive is stronger and hence LTV caps would have a more direct potential to also affect households' PDs.

One question that we address with the model is whether an LTV or a DSTI cap would be more effective in terms of reducing household sector loss rates (the product of PD and LGD), while taking account of the size of the policy-induced reduction in loan demand implied by the two measures and hence their macroeconomic feedback effects. The estimates for the seven EU countries for which we provide simulation results suggest that DSTI caps appear to be more effective in reducing household risk parameters as the required cap implies systematically less of a policy-induced shock to loan demand, hence resulting in less pronounced macro feedback effects in the short-term and in turn less second round deterioration for households' risk parameters.

1 Introduction

In the aftermath of the global financial crisis and the ensuing recessionary phase, central banks have significantly loosened monetary policy, both by conventional and unconventional means. More recently, some prominent commentators have argued that many advanced economies have entered a period of secular stagnation, whereby inflation would be expected to remain at low levels for long while potential output is falling for structural reasons.[1] In such an environment, monetary policy is likely to remain accommodative for a prolonged period to help moving inflation back toward its target and support the economic recovery. The significant liquidity creation associated with exceptionally loose monetary policy could, however, have unintended side effects on financial stability. To address the potential build up of financial imbalances under such circumstances, targeted macroprudential policy measures could help alleviate some of the strains on monetary policy. The hope is that they can help fine-tune, i.e. counteract the externalities arising from monetary policy action, both along a time and cross-section dimension, with the latter being particularly relevant in Europe whose business and financial cycles remain de-synchronised across countries to an extent, while monetary policy is centrally defined.

In policy circles, topics related to macroprudential policy are high on the agenda. See for instance three speeches[2] given by Vítor Constâncio, the ECB's Vice President, in February, April, and July 2015, highlighting at all occasions the importance of strengthening macroprudential policy in Europe. The emphasis is on the need for preventing fluctuations in financial cycles, i.e. to not only conduct macroprudential policy for the sake of enhancing the resilience of financial institutions. Moreover, emphasis should be put on lending standard-related, i.e. borrower-based, measures that unlike capital-based measures are not yet properly embedded in European legislation.

A subset of macroprudential instruments has been anchored in the Capital Requirements Regulation (CRR) and most recent Directive (CRD IV), where the Systemic Risk Buffer and other measures under Article 458 are available since some time already.[3] The ECB has a "top-up" right for such measures, meaning that it can impose stronger requirements beyond what national supervisors propose to set. Other measures will be phased in gradually, such as buffers for global or other systemically important institutions (referred to as G-SII and O-SII buffers respectively).[4] The measures that are embedded in the CRR/CRD IV are largely the capital-related ones, while the use of borrower-side measures is not currently envisaged to be centrally led, including most notably

[1] See e.g. Link for a compilation of articles related to the topic of secular stagnation.

[2] At the Conference on "The macroprudential toolkit in Europe and credit flow restrictions", organised by Lietuvos Bankas in July 2015, see Link; at the joint conference organised by the European Commission and the European Central Bank "European Financial Integration and Stability" in April 2015, see Link; at the Warwick Economics Summit in February 2015, see Link.

[3] Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013. Details about the CRR/CRD IV can be found at Link.

[4] See Link for the EBA's guidelines for the identification of global systemically important institutions (G-SIIs). The CRD IV requires G-SIIs to hold higher capital levels in order to contain the risks they pose to the financial system and the impact that their potential failure may have on sovereign finance and taxpayers, a circumstance that is currently referred to as 'too big to fail'.

caps on LTV or DSTI ratios.[5]

Quite some conceptual work has started to appear related to capital- and borrower-based macroprudential policy and the channels through which they are expected to work; see Cerutti et al. (2015), IMF (2013), Nier et al. (2012), Kannan et al. (2012), Kuttner and Shim (2012), Shin (2011), Christsensen (2011), IMF (2011), N'Diaye (2009), Borio and Drehmann (2009), and Dell'Ariccia and Marquez (2006). Useful literature overviews can be found also in Galati and Moessner (2011) and more recent in Galati and Moessner (2014). On the interplay between monetary and macroprudential policy, Unsal (2011) is a useful reference. The author analyses the relation between monetary policy and macroprudential regulation in an open economy DSGE model with nominal and real frictions, with the key finding being that macroprudential measures can usefully complement monetary policy. Even under an "optimal policy" which calls for a rather aggressive monetary policy reaction to inflation, introducing macroprudential measures is found to be welfare improving. Mendicino (2012) develops a business cycle model with credit friction and shows that countercyclical LTV ratios in response to credit growth can smooth the credit cycle.

On the empirical model side research is evolving though still quite scarce. Lim et al. (2011) use data from 49 countries to evaluate the effectiveness of macroprudential instruments such as LTV ratio caps in reducing systemic risk over time and across institutions and markets. Their results suggest that many of the most frequently used instruments are effective in reducing pro-cyclicality and the effectiveness is sensitive to the type of shock that the financial sector faces. Based on these findings, the paper identifies conditions under which macroprudential policy is most likely to be effective, opposed to conditions under which it may have little impact. Crowe et al. (2011) find a positive association between LTV at origination and subsequent price appreciation using state-level data in the US. Almeida et al. (2006) provide evidence that economic activity is more sensitive to house price movements if LTV is higher. Lamont and Stein (1999) provide evidence that economic activity is more sensitive to house price movements at times when aggregate LTV ratios are higher.

Hong Kong is an example of a country that has been subject to close scrutiny and impact assessments for some time. A list of impact studies includes e.g. Gerlach and Peng (2005), Ahuja and Nabar (2011), Wong et al. (2011), Funke and Paetz (2012), and Wong et al. (2014). The evidence overall suggests that LTV cap tightening in Hong Kong since 2009 has dampened both borrowers' leverage and credit growth and that lower leverage has played a role in strengthening banks' resilience to property price shocks. Moreover, the effect on loan growth is found to be state-dependent due to loan market disequilibrium, with a much stronger impact on loan supply than on demand, suggesting that calibrating borrower-side instruments to curb loan growth needs an accurate estimate of both loan demand and supply. This can pose challenges for policymakers. Finally, there is some evidence

[5] The meanwhile also evolving and quite significant literature related to measuring the cost and benefits of capital-related policy measures is a separate strand that we do not want to start citing comprehensively as it is not the main topic of our paper. Just as an entry point, the BIS (2010) for instance is useful as it compiles the results from a large number of models that were all meant to inform the expected cost and benefit of enhanced capital regulation. The finding overall and evolving consensus in the literature is that the functional relation between bank capitalization and welfare is concave, such that there would be an optimal level of capital, which according to the estimates ranges above current levels, between roughly 12% - 20% or more.

for rather low responsiveness of housing demand to caps on LTV ratios, which is suggestive of a weak direct pass-through of LTV policy to the property market.

Further sorting along the geography of the applications, research has been done for the Irish case. See e.g. Cussen et al. (2015) who conduct a micro-simulation exercise based on loan-level data to quantify the impact of various caps on loan volumes, to then — in a second step — employ a BVAR to simulate the macro impact for Ireland. Further related work for Ireland can be found in Hallisey et al. (2014), Lydon and McCarthy (2013) and Kelly (2011). For New Zealand, see e.g. Price (2014) and Bloor and McDonald (2013). The latter have developed a BVAR to conduct *ex ante* counterfactual analyses prior to the introduction of borrower-based policies (with the approach being adopted by Cussen et al. (2015)). For Korea, Igan and Kang (2011) find that LTV and DTI caps help contain house price growth and transaction activity and the imposed limits work, notably, via expectations. The latter aspect, i.e. the importance of an expectation channel, is also highlighted in Lambertini et al. (2011) who develop a model of the housing market that incorporates expectation-driven cycles to then show that countercyclical LTV rules responding to credit growth can reduce the volatility of loans and the loan to GDP ratio.

The contribution of our paper, seen against this evolving strand of the literature, is to develop a fully integrated micro-macro model, a first to the best of our knowledge of its kind, to assess the efficacy of borrower-based instruments, such as LTV or DSTI caps. We employ household-level survey data which forms the basis for the micro component of the model. Similar use of borrower-level data has been made only in the aforementioned model for Ireland (Cussen et al. (2015)) and in Michelangeli and Pietrunti (2014). The difference to our framework, however, is that Michelangeli and Pietrunti (2014) look at the evolution of household indebtedness and debt service ratios, while not aiming to obtain risk measures such as probabilities of default or loss given default, which is an essential output from our model. Likewise for Cussen et al. (2015); here the authors use micro data to calibrate a policy-induced loan volume shock whose impact is assessed with the BVAR. The impact goes only from the micro shock to macro, and not vice versa, however. The novel features of our model — the Integrated Dynamic Household Balance Sheet (IDHBS) model — can be summarised as follows:

1. Primary output of the model are measures of probability of default and loss given default at the household level. The risk parameter estimates can be obtained either with or without the imposition of LTV or DSTI caps, thereby allowing for a quantified impact assessment of the caps at self-defined thresholds.

2. The household-level risk parameters are a function of macroeconomic and financial factors which drive the size and structure of households' balance sheets. It is a structural model approach in that sense. Interest rates, unemployment rates, income, house and stock prices, and others, are used to steer the household members' and household parameters and thus their implied PDs and LGDs.

3. Policy cap-induced loan demand shocks are allowed to influence macroeconomic and financial variables which in turn are allowed to feed back to households' risk parameters. We allow for

a two-way interaction between the macro and micro sphere.

4. The household-level risk parameters can in the end be aggregated to household sector (country) level and be attached to bank balance sheets to assess the impact of borrower-side macroprudential policy measures on the capital position of financial institutions.

The household data is sourced from the Eurosystem Household Finance and Consumption Survey (HFCS) which is a decentralized survey of the Eurosystem in which the participating national central banks or national statistical institutes (depending on the country) conduct their own wealth survey.[6] A number of studies uses the survey data for the primary purpose of measuring household vulnerability.[7] Most of these studies operate with the concept of a *financial margin* which measures a household's ability to cover periodic expenses by periodic income, i.e. it is a net *flow* measure. E.g. Albacete et al. (2014) and Ampudia et al. (2014), as many others, define it as disposable income minus basic consumption and debt service. If the financial margin, defined as such, turns negative it means that liquid assets, in the form of sight or term deposits for instance, would need to be drawn down to cover expenses, i.e. liquid asset stocks shrink. In the IDHBS model we employ a measure of liquid assets, i.e. a *stock* measure, which is driven by the financial margin (flow measure) over time, as a basis for computing the propensity of households to be late with their debt payments. Details will follow in Section 2.

The macro model component of the IDHBS is based on a Global Vector Autoregressive (GVAR) model structure.[8] This modelling framework lends itself naturally to an assessment of how much credit demand or supply shocks, as induced by macroprudential policy instruments applied in one country, can spillover to other countries.[9] One channel through which cross-border effects can arise is through foreign banks that would adjust their lending behaviour to a country that imposes a cap, for the bank to possibly divert away its resources to other countries. Price and volume effects can thus be expected to materialise not only in the country to which macroprudential policy is applied.[10] Moreover, even if a bank or banking system was purely domestically active, by assumption, curtailing loan demand via the imposition of caps could result in cross-border spillover at the macro level through the trade channel. These channels are well captured by the GVAR module as part of the IDHBS.

[6] See Link.

[7] See May et al. (2004), Johansson and Persson (2006), Vatne (2006), Herrala and Kauko (2007), Hollo and Papp (2007), Fuenzalida and Ruiz-Tagle (2009), Sugawara and Zalduendo (2011), Costa and Farinha (2012), Djoudad (2012), IMF (2012), Albacete and Lindner (2013), Albacete et al. (2014), Ampudia et al. (2014),and ECB (2014).

[8] A useful entry point to the GVAR literature is a recent survey paper by Chudik and Pesaran (2014), summarising all methodological and empirical development in the field over the past decade. The initial methodological contributions by Pesaran et al. (2004), Pesaran and Smith (2006) and Dees et al. (2007) were followed by a meanwhile significant number of empirical applications. Examples include Galesi and Sgherri (2009), Chen et al. (2011), Chudik and Fratzscher (2011), Bussiere et al. (2011), Eickmeier and Ng (2011), Binder and Gross (2013), and Gray et al. (2013). A so-called Mixed-Cross-Section (MCS) variant of a GVAR has been developed in Gross and Kok (2013) as well as further in Gross et al. (2016) and Behn et al. (2016).

[9] Capital-based macroprudential instruments can be seen as inducing bank credit supply shocks, while the use of borrower-based instruments implies a policy-induced credit demand shock.

[10] See also Ongena et al. (2013) in that respect.

The two main findings from our IDHBS-model-based analysis that we conduct for a subset of seven EU countries are the following: first, both LTV and DSTI caps have the potential to curb household sector risk parameters while being accompanied by macro feedback effects, implying that house prices, credit, and real activity measures grow at smaller rates, which reflect the 'desired' short-term cost of the measures; second,DSTI caps appear to be more effective than LTV caps from the perspective of reducing household risk parameters while implying less pronounced macro feedback effects.

We shall emphasise here that our notion of 'more effective' is specific indeed to the idea that a measure implies *less* macro feedback effects in the short term while rendering the household sector more (equally) resilient in the long term.[11] One might want to employ a different definition of 'efficacy' whereby a policy measure would be more effective if it helps compressing for instance house price growth more than another instrument in the short term, i.e. neglecting the long term and in that sense implying a larger cost in terms of price, wealth and possibly real effects. Yet, we prefer our definition of efficacy because it has a *net* benefit perspective, i.e. it includes a long-run perspective as well. We shall note that our macro model and the framework overall is able to well quantify the *short-term* macroeconomic costs, while it is not yet sufficiently developed to assess the long-run benefits in terms of macroeconomic developments in response to policy. For that reason, we take the household risk parameters and their responses as a measure of benefit. A long-run net benefit would, consequently, be higher for those measures that generate less short-term costs along with the same benefit in the long run, thereby making DSTI caps more effective than LTV caps in the long run according to the estimates that we present later in the paper.

Studies such as Lim et al. (2011), as mentioned above, find that LTV caps lead to a reduction in credit and asset price growth in many countries where they were historically employed. DTI caps are able to contain credit growth, while asset price growth tends to be less responsive. Moreover, the panel model estimates that the authors present suggest that both LTV and DTI caps reduce the procyclicality of credit with GDP and leverage (assets over equity) with GDP. Concerning the procyclicality between credit and GDP, the estimated effect on the DTI interaction term appears to be more sizable than the one on the LTV term. There are two conceptual differences to our model structure and analysis: first, the effectiveness of the instruments is measured in Lim et al. (2011) and others with respect to how the correlation of credit and GDP, or leverage and GDP is lessened after imposing the caps. Hence, the focus is on the ability of the measures to reduce financial accelerator effects; second, the policy measures are controlled for in their model (and numerous other references mentioned above follow the same approach) with dummies, i.e. there is no account for the actual *calibration* of the instruments. Seen against Lim et al. (2011) and others mentioned above, it should be emphasised that the IDHBS model starts from an assumed (calibrated) loan demand shock in response to an LTV or DSTI cap. Macro and asset price responses then depend on the extent to which they had a stable empirical relationship with credit historically.

In Section 2 we present the model and all its components. In Section 3 we present the results

[11] For clarifying what 'equally resilient' means, the concept of 'loss rate equivalence' will be introduced later in the paper.

from a series of simulations for seven European countries, to show the impact of LTV and DSTI caps as well as to answer which of the two measures is more effective (based on a criterion that will be discussed in the section). Section 4 concludes.

2 The model

2.1 Structure of the household balance sheet and P&L

We start by outlining the structure of the balance sheet and profit and loss (P&L) of a household, to thereby see which components need to be modelled subsequently. Figure A shows a schematic picture of the household balance sheet. Assets can be grouped into real (A^R) and financial (A^F), with real assets comprising houses, land, cars and other tangibles. The market value of houses and land we subsume in the variable H. The residual of all other real tangible valuables will be denoted as V^R.

Financial assets include cash, sight and term deposits (D^{SI} and D^{TE}), holdings of sovereign, corporate, or other bonds (B), shares in listed companies (S) as well as again a residual of items (V^F) which may include savings that are accumulated in pension funds, insurance funds, or the like. On the liability side households may face an amount of debt (L) which can be outstanding in the form of a mortgage (L^M), i.e. the particular purpose of a purchase of a house, including possibly land, or the form of un-collateralised debt to which we refer as consumer credit (L^C). Total assets are the sum of real and financial assets ($A = A^R + A^F$) and the gap between the value of assets and outstanding debt is the net wealth ($E = A - L$) of the household.

Turning to the P&L, i.e. the income and expense stream that a household faces which makes its balance sheet size and structure flow over time, we first define the gross income from self-employed or employed work as INC^G. The net income after tax we denote as INC^N which equals gross income less an amount of income tax implied by a tax rate r, that is, $INC^N = INC^G \times (1 - r)$. In case a household member is unemployed, it receives a net unemployment benefit U^N.

The periodic change in the market value of liquid assets such as bonds and stocks will be denoted as RET^B and RET^S, respectively for bonds and stocks. We assume that even though households would not sell bonds or stocks during the forward simulation that we will conduct with the model, the value change in these assets will be immediately recognised through the household's P&L (using bank jargon here, we *mark-to-market* the value of these assets). Deposits are assumed to yield a return as well, denoted as RET^D.[12] On the liability side, the periodic expense components relate to outstanding mortgage debt (EXP^M) or consumer credit (EXP^C).

[12] In the current version of the model we will hold the remuneration of deposits constant.

Figure A: The household balance sheet

<table>
<tr><th colspan="2">Assets</th><th colspan="2">Debt and equity</th></tr>
<tr><td rowspan="2">A^R</td><td>House/land (H)</td><td>L^M</td><td>Mortgage debt</td></tr>
<tr><td>Other real valuables (V^R)</td><td rowspan="4">L^C</td><td rowspan="4">Consumer credit</td></tr>
<tr><td rowspan="6">A^F</td><td>Cash</td></tr>
<tr><td>Sight deposits (D^{SI})</td></tr>
<tr><td>Term deposits (D^{TE})</td></tr>
<tr><td>Bonds (B)</td><td rowspan="3">E</td><td rowspan="3">Equity</td></tr>
<tr><td>Stocks (S)</td></tr>
<tr><td>Other financial valuables (V^F)</td></tr>
</table>

Note: The schematic picture of the household balance sheet is useful to see what elements will be modelled and simulated forward in time using the various modules of the IDHBS model.

2.2 The model structure

Figure 1 summarises the model structure. It is a modular structure, consisting of two database inputs and six core modules that are labeled A-F. We describe these components in the following.

HFCS Micro Database

The Eurosystem Household Finance and Consumption Survey (HFCS) is a decentralized survey of the Eurosystem in which all participating institutions (national central banks or national statistical institutes) conduct their own wealth surveys. The HFCS provides the Eurosystem with harmonised micro-level data on euro area households' finances and consumption. The survey is conducted with a frequency of 2 or 3 years, with the most recent one that the current model calibration and assessment is based upon being from 2011.

The HFCS database is composed of questions referring to the *household* as a whole — answered only by a single person: the main respondent — and those targeted to individual *household members* — asking for basic demographic information based on a personal questionnaire for all participating household members that are older than 16. The survey part covering household-level questions encompasses real assets and their financing, liabilities and credit constraints, private businesses and financial assets, intergenerational transfers and gifts and consumption/savings. Questions to individuals cover employment, future pension entitlements and labour-related income (other income sources are covered at the household level). The distinction between household member and household-level variables is important and will become more obvious once the various modules of the IDHBS model are described in the following.

Table 1 lists all variables that are taken from the Survey Database and needed as input for the IDHBS model. It is useful as a reference in particular for the description of Modules B and D in the following.

Macro Database

The macro database covers ten variables for 28 EU countries, i.e. 280 time series, with a quarterly frequency over the 1995Q1-2014Q4 period. The variables are the input to the macro model component of the IDHBS and include the following: Unemployment rates, long-term interest rates (10-year benchmark government bond yields), stock price indices, nominal compensation per employee, nominal residential property price indices, nominal GDP, a GDP deflator, short-term interest rates (3-month money market interest rates), nominal domestic credit from financial institutions to the private sector as well as nominal loan interest rates. The loan volume and price variables have a locational definition, i.e. refer to credit that is supplied from banks (whether domestic or via branches, subsidiaries or direct cross-border lending from foreign banks) to the resident households and non-financial corporations of a country. Along with the macro-financial time series, a significant additional part of the macro database contains the trade and other variables that are an important input to the model structure for the calibration of the weights which are needed to set up the GVAR structure.

Module A: The GVAR

The Global Vector Autoregressive (GVAR) model serves to capture all domestic and cross-border dependencies of the aforementioned ten variables. Based on the estimated model which comprises 280 equations, a stochastic forward simulation can be conducted to generate a large number of (100,000) consistent multivariate, multi-country forward paths up to a self-defined horizon. The paths are consistent in the sense that historical dependencies between variables within and across countries are reflected in the simulated forward paths. In Annex A the GVAR model structure is described in more detail.

Module B: Logistic model for employment status of household members

The logistic model for the employment status operates at *household member-level*. The household member employment status is the dependent variable. Retirees and students are excluded and only employed, self-employed and unemployed household members are considered. No distinction is made between employed and self-employed in the model, i.e. the two groups are pooled into one, thus the model is a binomial logistic model for each country distinguishing between being employed and unemployed for every household member.

The logistic regression to estimate the probability for each household member of being employed starts from the definition of a latent variable y_t^i. A household member i is employed at time t if y_t^i is larger than zero and (s)he is unemployed otherwise. The latent variable is a function of some household member characteristics (x_j^i, with the subscript j denoting the characteristic) and a random variable ϵ_t^i that has a standard logistic distribution.

$$y_t^i = \alpha + \beta_1 x_1^i + \beta_2 x_2^i + ... + \beta_J x_J^i + \epsilon_t^i \tag{1}$$

Under these assumptions the probability for a household member to be employed is:

$$ProbEmp^i = \frac{1}{1 + \exp(y^{i*})} \tag{2}$$

where y^{i*} is:

$$y^{i*} = \alpha + \beta_1 x_1^i + \beta_2 x_2^i + ... + \beta_J x_J^i \tag{3}$$

The explanatory variables include age, gender, marital status, the highest level of education completed, and whether the household member has its origin in the same country or not.[13] All intercept and slope coefficients of the logistic model are country-specific, i.e. the logistic model is effectively estimated country-by-country. The coefficients β_j are estimated using a standard maximum likelihood method.

Overall, the purpose of the logistic model engine is to endogenise the employment status of individual household members and use its implied probabilities of being employed in the subsequent Module C to simulate a distribution of outcomes for the employment status for all individual household members.

Module C: Employment status simulator

This module receives two inputs: the logistic model estimates from Module B along with the simulated forward paths from Module A (GVAR) for the aggregate unemployment rates at country level.

The role of Module C is to simulate the employment status of household members from the logistic model – given the fix household member characteristics such as age (which moves forward deterministically year by year over the simulation horizon), gender, etc. – while adjusting the intercept term of the logistic model for each country to match the aggregate unemployment rate

[13] Ideally, a duration of (un)employment variable would be included in the model which is, however, not available in the household survey database.

forward paths coming from the GVAR. This intercept adjustment is done for all joint multi-country forward paths from the GVAR sequentially (or the one specific baseline or adverse multi-country paths).

A stochastic simulation from a binary response model would start from drawing uniform random vectors of size $N \times 1$ from the [0,1] interval and assign a household member the employment flag whenever the uniform random number is larger than its estimate for the probability of being employed. A problem with this sort of stochastic simulation would be, however, that the prevalence in employment or unemployment status for the household members would be *random* along the scenario horizon, i.e. household members would too often switch back and forth between being employed and unemployed which is not realistic and would distort the subsequent assessment as to how often a household's liquid assets are insufficient to service its outstanding debt.

To address this issue, an important additional technical feature is embedded in Module C. It takes an aggregate duration of unemployment parameter (country-specific) into account while conducting the forward simulation. The error term of the logistic model is assigned a *persistence parameter* which is set such that the aggregate duration of unemployment is matched. This procedure works as follows.

We start from a set of uniform random numbers that we transform into white noise (η_t^i) with an inverse probability distribution (standard normal for instance):

$$\begin{aligned} \epsilon_1 &= \eta_1 \\ \epsilon_2 &= \rho\epsilon_1 + (1-\rho)\,\eta_2 \\ &\dots \\ \epsilon_t &= \rho\epsilon_{t-1} + (1-\rho)\,\eta_t, \forall t \geq 2 \end{aligned} \tag{4}$$

Taking into account that these variables ϵ_t are not independent anymore, their variances are not one as in the case of η_t. Instead, their variances are:

$$Var(\epsilon_t) = \rho^{2(t-1)} + (1-\rho)^2 \frac{\rho^{2(t-1)} - 1}{\rho^2 - 1} \tag{5}$$

Using the same probability distribution, but with this alternative variance measure, we can transform our ϵ_t variables into probabilities again. The main difference is that these new probabilities are not serially uncorrelated, but persistent to some extent, with the parameter ρ allowing us to steer the degree of persistence.

We calibrate ρ such that the implied average duration in unemployment matches the observed unemployment duration estimates that can be found for instance in the OECD data warehouse.[14]

[14] More information on the calibration of this and various other metadata parameters will follow in Section 3.

The average duration parameters that we match are country-specific.

In addition to the degree of persistence we also need to control the aggregate unemployment rate when it comes to a scenario conditional forward simulation. As hinted to above, we do so by adjusting the intercept of the model to match a desired aggregate unemployment rate.

Module D: Household balance sheet simulator — Default detection and LGD calculator

The household balance sheet module operates at *household-level*, i.e. the household member information coming from Module C (employment status simulator) is combined by assigning household members to their households. It is therefore the combined household balance sheet that serves as a basis for the measurement of default and LGDs, while the P&L of the household – in particular the income part of it – is driven by the household members, their employment income or unemployment benefit respectively.

With the variable abbreviations that were defined above we can define liquid assets ($LiqA$) and subsequently how they evolve over time. Liquid assets are composed of cash and cash equivalents C, as well as bond (B) and stock holdings (S).[15]

$$LiqA_t = C_t + B_t + S_t \tag{6}$$

The periodic change of liquid assets is determined as depicted in equ. 7.[16]

$$\Delta LiqA_t = \Delta B_t + \Delta S_t - min(L_t, EXP_t) + \begin{cases} INC^G_{n1,t}(1-r)(1-l^e), & \text{if employed} \\ U^N_{n2,t}(1-l^u), & \text{if unemployed} \end{cases} \tag{7}$$

First, the change is driven by periodic movements in the market value of corporate or sovereign bonds (ΔB_t) as well as value changes of outstanding shares (ΔS_t). Second, an outstanding loan amount L_t has to be serviced by a periodic debt repayment amounting to EXP_t, such that outstanding debt moves period by period as $L_t = L_{t-1} - EXP_t$ until L_t falls to zero once all debt is repaid. The portion of gross income spent to cover living expenses is denoted as l, with that percentage possibly being specific to whether a household member is employed or not, denoted by the superscripts e and u, respectively.[17] The expenses for living imply a cash outflow, while employment

[15]Other forms of assets besides cash and sight deposits that we consider 'cash equivalents' and subsume for that reason in C include the amounts accumulated in savings accounts, mutual funds, and voluntary pension funds. The rationale for including these is that such buffers might be drawn down in case that a household's periodic income does not suffice to cover periodic expenses, including debt repayment. They are considered 'liquid enough' to be converted to cash within a short period of time.

[16]As hinted to in the introduction, this periodic change comes closest to what has been defined as the financial margin in the literature as of yet.

[17]For the simulations that we present later the cost of living percentage is set equal for both employed and unemployed household members.

income or an unemployment benefit imply a periodic cash inflow. We assume that households do not use their cash inflows through income or unemployment benefits to invest additional funds in bonds or stocks throughout the simulation horizon. They may only draw the holdings down, i.e. sell bonds or shares in the secondary market at current market prices, in case that all other cash and cash equivalent funds are insufficient to meet their periodic debt service payments.

If liquid assets become negative in some period along the simulation horizon (which they cannot in reality, but only in the course of the simulation), the household is assigned a *default flag*. Once a household receives the flag we do not simulate the household and its members' income and expenses further in time, i.e. we do not allow it to recover and resume its debt repayment by assumption. We shall note that the definition of 'default' does not mean that a household would be insolvent, i.e. it is not meant to refer to literal bankruptcy. It is related instead to the household's ability in the short term to repay its outstanding debt to the bank, i.e. the flag signals that a household was illiquid, rather than insolvent.

Along with the default indicator that is tracked for each household, an LGD is computed continuously. Provided that there is a default, we consider two possibilities: either the bank confiscates the house in the near future or the household recovers and continues repaying the mortgage loan.

$$LGD = P^C LGD^C + (1 - P^C) \times LGD^{NC} \tag{8}$$

with P^C being the probability of confiscation and LGD^C and LGD^{NC} being the LGD under the two scenarios of confiscation or no confiscation. The probability of confiscation and the LGD under the recovery scenario are defined exogenously whereas the LGD under the confiscation scenario is evolving dynamically over the simulation horizon as a function of house prices (in particular the house price change up to the end of the confiscation period).[18]

We define the discount rate as follows:

$$Discount = 1/(1 + LTN)^{Confiscation-time} \tag{9}$$

where LTN is the long-term interest rate by the time of confiscation. The value of the house at confiscation time ($V^{T^{confisc}}$) is projected by aligning it with the house price move (from the GVAR) between the time of default ($T^{default}$) and the time of confiscation ($T^{confisc}$), that is,

$$V^{T^{confisc}} = e^{ln(V^{T^{default}}) + ln\left(\frac{HP^{T^{confisc}}}{HP^{T^{default}}}\right)} \tag{10}$$

where HP is the country-level house price variable from the GVAR. The LGD under the confiscation scenario is:

[18] The probabilities (weights) for the two scenarios, confiscation as opposed to no confiscation, are currently set to 95% and 5%, respectively, by assumption.

$$LGD^C = 1 - min[V^{T^{confisc}} + V^R, L^M(1 + AdCost)]/L^M \times Discount \tag{11}$$

where $AdCost$ reflects an administrative cost component as a percentage of the outstanding loan amount.

Concerning the variables that are relevant to determine the forward path of the household balance sheet, we now describe how the country-level macro variables from the GVAR engine are used to steer the household and household member-level variables.

1. The *compensation per employee* variable from the GVAR is used to steer the income path for employed household members. Log percent changes of income from the GVAR are attached to the household members' quarterly income starting points.
2. *Stock prices* from the GVAR are used to re-value the stock holdings of a household (pooled from household members). Log percent changes of equity prices from the GVAR are attached to the household level value of stocks at the survey date.
3. *Long-term interest rates* (10-year benchmark government bond yields) from the GVAR are used to steer the value of bond holdings of the households. Absolute changes of long-term rates quarter-on-quarter are used to re-compute the market value of the bonds. This variable serves as well as input to the LGD formula (as a discount factor).
4. *House prices* are used to value the house along the simulation horizon, which serves as direct input to the LGD formula, as outlined above.

Apart from these four inputs that flow directly from Module A to Module D, there is the indirect connection via Module C (employment status simulator), via the aggregate unemployment rate at country level. To recall, the forward paths generated in Module A feed through Module C to D and directly to D in a consistent manner, i.e. the simulated employment status for individual household members for a given simulation round going from Module C to D is consistent with the macro variables' path flowing from Module A to D. This is essential as it allows properly capturing the dependencies between all variables that are involved in the macro and micro part of the model.

Module E: Counterfactual macroprudential policy simulations

The counterfactual policy simulator operates on LTV ratio caps and DSTI ratio caps. The module takes the simulated default and LGD forward paths from Module D as input and, as a first step, excludes the households whose LTV/DSTI ratios stand above a self-set threshold. Then the PD/LGD/LR aggregator is re-run on the reduced population. The imposition of LTV constraints operates on initial LTV ratios, i.e. initial sizes of the mortgage loan at the time of acquisition of the house along with the initial value of the house. The DSTI cap can in the current version of the model be based only on current DSTIs, i.e. the ratio of the current debt repayment amount relative to current income of a household by the survey date.[19]

The HFCS contains the information as to when a mortgage loan was granted to a household. For the imposition of the initial LTV constraint, a reference period (one or multiple years) can be chosen in the model; only the households whose mortgages were granted during that period can then be excluded.

An additional simulation mode aims to account for the macro-feedback effects that likely arise from imposing LTV/DSTI constraints as a result of reduced loan volume growth as a part of the household population is prevented from obtaining a mortgage loan. This policy-induced negative credit demand shock is calibrated based on the HFCS data, specifically as the volume of household mortgages that are being excluded given the LTV/DSTI ratio cap relative to the total volume of mortgages granted in the reference period. The resulting credit demand shock is taken as input to Module A (GVAR) for a given country to simulate the responses of all model variables (sign constraints are involved to identify the impulse responses as credit demand shocks). The GVAR model structure is useful to gauge – in this particular context of country-specific LTV/DSTI ratio caps – also the possible cross-border spillover effects through the trade channel at country level, or financial market spillovers which may cause the valuation of stock and bond holdings of households to react beyond the national borders where a policy measure was introduced.

The channels through which primary as well as secondary feedback effects may occur are manifold. The aggregate probability of default of households in the population may fall if high LTV households would not be granted a loan, and if the high LTV ratio characteristic correlates with lower financial margins of these households, or possibly a higher propensity for those becoming unemployed (to be assessed empirically). The primary impact on aggregate LGDs would be rather mechanic, namely negative as lower aggregate loan to value ratios imply that more collateral is available to back the household loans and hence imply lower LGDs. The combined effect on loss rates from a credit provider perspective is likely negative (i.e. loss rates fall) considering only the first round effects.

Secondary effects can be split into *short-term* and *medium-term* secondary effects. One sort of short-term secondary effect — which can be assessed based on the current version of the IDHBS

[19] Initial DSTIs referring to the time of mortgage loan origination would be the more ideal measure which are, however, not available in the HFCS as both the income nor the debt service amount at origination are included in the survey. A concern that may arise is that the use of the current DSTI based on which a portion of the mortgage debtor population is excluded once a DSTI cap is imposed might be biased, as we would tend to exclude those households who experienced an income shock (i.e. got unemployed) prior to the survey date. We conducted a robustness check in that respect by applying the DSTI caps only to the portion of the households whose household heads are employed by the survey date and found that the impact estimates that we present later do not change materially; in particular does the conclusion that DSTI caps are more effective than LTV caps (according to a criterion that will be defined later) not change. One possible explanation for that finding is that households with high DSTI ratios are also the ones with higher absolute income which correlates with a lower probability of getting unemployed. This robustness check notwithstanding, the more ideal solution would be to use 'initial' DSTI ratios if they were available. One can consider 'back-casting' the current DSTI ratios in a future version of the model, with income for instance being aligned with aggregate income growth backward in time; for the current version of the model we did not deem such back-casting mechanism robust and therefore not useful enough, however.

model — may arise as a result of reduced credit demand in response to which economic activity may drop to an extent due to less construction. GDP would drop and unemployment rates may rise to some extent which would imply some counteracting upward pressure on PDs for those households that get unemployed. Downward pressure on house prices or at least less intense positive growth (desired by the policy) would let LGDs rise as the expected value of housing collateral would fall.

An additional aspect that needs to be kept in mind with respect to these short-term secondary effects is related to the loan interest rate (specifically mortgage rate) responses. If the loan volume shock is to be seen as a credit demand shock, loan interest rates would tend to fall, for banks to thereby stimulate demand. Lower interest rates on new business, or lower rates for existing business in variable rate regimes, might imply some further downward pressure on PDs as it would reduce the households' debt repayment burden to some extent. The extent to which banks would be willing or able to reduce loan interest rates to stimulate new business would likely depend on during which phase in the business cycle the, say LTV, policy is conducted. During boom times, banks' net interest margins are more sizable, giving them some room for downward-adjusting loan interest rates.

Other short-term secondary effects may arise as a result of reduced household sector PDs and LGDs, and, consequently, loss rates for banks. Banks that face lower loan losses can employ their funds more productively and invest in profitable projects which would imply a positive contribution to aggregate economic activity. Moreover, households with more stable balance sheets, as being less inclined to take on sizable (oversized) debt amounts, would contribute to develop a more sustainable forward path for households, with their PDs being lower in the long run.

Overall, considering the various channels and their implied signs and sizes of possibly counteracting effects on PDs and LGDs, the net effects of the primary and secondary impact on the risk parameters would need to be assessed, as a function of the initial LTV/DSTI thresholds and country-by-country to account for differences in sensitivities of macro and financial variables to credit demand shocks.

Module F: Link to bank balance sheets

The final element in the module chain is Module F which links the PD/LGD/LR paths (and loan volume paths) of the household segments for all countries to banks' balance sheets. The banks' mortgage portfolios in their home countries as well as possibly their cross-border exposures through subsidiaries are assigned the counterfactual (either purely scenario-conditional or as well policy conditional) risk parameters from Modules D/E to assess the Common Equity Tier 1 (CET1) capital reaction.

The household mortgage-specific nonperforming loan (NPL) stock evolves as follows:

$$NPL_t = NPL_{t-1}(1 - w_t) + PD_t(L_{t-1} - NPL_{t-1}) \tag{12}$$

where L_t are gross loans and $L_t - NPL_t$ is assumed to equal the exposure at default EAD_t.[20] The gross loan stock is allowed to grow (or shrink) at rate g, i.e. we allow for a dynamic evolution of the balance sheet as the LTV/DSTI cap policy would imply a reduction in gross loan volumes, i.e. non-renewal of existing loans once they mature since less households would qualify for a mortgage. We assume that the write-off parameter w for NPLs equals zero.[21] Cures, i.e. the migration of loans from nonperforming back to performing status will be ruled out by assumption (mirroring the assumption that is also embedded in Module D).

Expected losses are calculated based on the standard formula:

$$EL_t = PD_t \times LGD_t \times EAD_{t-1} \tag{13}$$

where EAD_{t-1} is the exposure at default at the end of period $t-1$ (the beginning of period t).

The impact on risk weights is accounted for by employing the Basel formula for the household mortgage segment which translates PD, LGD and EAD parameters into risk weighted assets (RWA).[22] We compute an RWA amount as of end-year 2013 (denoted as $RWA_{2013}^{aggr,mortgage}$) and then for the scenario-conditional paths from the GVAR ($RWA_{2013+h}^{aggr,mortgage}$). The absolute difference between these self-computed forward paths of the RWA related to the household mortgage portfolio and the self-computed 2013 starting point is then applied to the 2013 RWA as observed at the bank-level (denoted as $RWA_{2013}^{bank,total}$).[23] Eq. (14) indicates how the RWA forward paths are computed.

$$RWA_{2013+h}^{bank,total} = RWA_{2013}^{bank,total} + RWA_{2013+h}^{aggr,mortgage} - RWA_{2013}^{aggr,mortgage} \tag{14}$$

Apart from the RWA impact, Module F also accounts for forgone interest income that the simulated default flows imply. To that end, an effective interest rate is computed at bank level for the 2013 starting point which is then aligned with the interest rate path from the GVAR (Module A) throughout the simulation horizon. The loan interest rate proxy, which is computed as the ratio of interest income over interest bearing assets, is then multiplied by the default flows that are being simulated from the GVAR and the resulting forgone interest amounts subtracted from capital year by year along the simulation horizon.

The assessment is overall partial as only the implied losses and forgone interest income for the

[20] The exposure of default (EAD) concept is a forward-looking variant of performing loans (PL) which are equated here for the sake of illustration.

[21] For value ranges that are commonly observed for write-off rates, the results that we later present remain robust, i.e. change only beyond the first decimal place of the capital impact estimates for the banks in our sample.

[22] See CRR (2013), Article 153 point 1 (iii) (pg. 97).

[23] The reason for computing a 2013 starting point ourselves and then attaching the absolute changes to the 2013 bank starting point is that the RWA formula is not expected to exactly replicate the RWA reported by a bank due to the nonlinear nature of the RWA formula that banks would apply at line level while we use it at portfolio level. When being applied at different levels of granularity, the formula gives slightly different estimates of RWA total for a portfolio.

mortgage loan portfolios are under scrutiny – either conditional or not on the policy measures. All other loan portfolio segments as well as mark-to-market valuation effects for the banks' trading portfolios in response to stock and bond price changes are currently disregarded. It would – model structure-wise – be well possible to account for these and other effects, though on purpose they are not accounted for to single out the effects on the capital position of banks through the income and loss generated from only their mortgage portfolios when either considering or not the imposition of LTV/DSTI ratio caps.

3 Simulation results

We present empirical results for seven countries: Austria, Belgium, Germany, Luxembourg, Portugal, Slovenia, and Slovakia. Table 3 reports the number of households and household members for the seven countries under scrutiny, showing the count for the total population comprised by the survey and the subset of which has mortgage debt outstanding and for which an initial LTV ratio was available. In Annex B we provide further details about the estimated logistic model underlying Module B.

We start by running the IDHBS model under a baseline mode with a 1-year horizon. The effective simulation horizon for Module A (GVAR) is set to 3 years because the liquidation time for housing collateral is assumed to be eight quarters. Thus, for households that happen to default at the end of the first year an LGD can be computed with the additional 8-quarter horizon, for which in particular the simulated house price path is required. The output from the model (Module D) is a PD and LGD baseline estimate for each household that has mortgage debt outstanding. Moreover, we obtain for each household member a probability of being employed (from Module B).

The aforementioned metadata parameters are summarised in Table 2 for all 15 countries that the survey comprises; though for only seven countries they will be needed now. The set of parameters include the average duration of unemployment for the total population per country (sourced from the OECD)[24], the cost of living which we derive as 1 minus the savings ratio (sourced from the European Commission (EC)'s Ameco database), an average implicit tax rate on labour which is the

[24]The duration of unemployment parameter could in principle be set more specifically conditional on some demographic characteristics of the population, with respect e.g. to age or gender which are two criteria that the OECD distinguishes between. Concerning age groups it should be noted, however, that for two of the groups (age 25-54 and 55+) the weighted average duration of unemployment (weighted by outstanding mortgage loan volumes) is close indeed to the duration of the total population. For the European aggregate, for example, the difference between the duration for the total population (15.3 months in 2014) and the weighted aggregate for the population older than 25 (15.9 months) amounts to merely 0.7 months (4.4%). The loan volume amounts granted to households whose heads are older than 25 constitute 95% of total mortgage loan amounts over all 15 countries covered by the survey. Hence, it would not have made a material difference for the simulation results when introducing some additional age grouping. Moreover, the differences for the duration depending on gender are minor, too. For the aggregate for Europe, the duration estimates for males and females in 2014 equal 15.2 and 15.3 months respectively (15.3 months for the total population).

ratio of taxes and social security contributions on employed labour income to total compensation of employees (from the EC's regular Synthesis reports), and a net replacement rate which captures how much net unemployment benefit persons that get unemployed earn relative to their previous net income (from the OECD).

The net replacement rate is converted first to a gross replacement rate via the tax rate assumption and then used in the model to generate hypothetical starting points for the unemployment benefit for all employed household members. In case that household members get unemployed in the course of the simulation, that starting point is used (and also chained by means of the income growth paths from Module A). Vice versa, the inverse of the replacement rate is used to generate hypothetical income starting points for the initially unemployed household members. One final parameter captures the portion of household mortgage debt relative to total private sector debt outstanding by 2013, which is based on bank balance sheet (BSI) statistics from the ECB. The parameter is needed to later scale the household mortgage specific loan demand shocks to total credit shocks, as total credit is contained in the GVAR model.

3.1 LTV versus DSTI caps — What is more effective?

A first question that we aim to address is by how much LTV caps and DSTI caps are able to reduce household PDs, LGDs and loss rates. We define a grid for the LTV cap, denoted as $LTVgrid$, spanning the range from 0.5 to 1.2, and for the DSTI cap, denoted as $DSTIgrid$, ranging from 0.1 to 1. The caps are imposed to compute the implied EAD-weighted PDs and LGDs for a country after the portion of the population whose initial LTV or DSTI stand above the assumed caps is excluded. A chart collection for each country is presented in Figures 2-8.

The first three charts down the first column show how PDs, LGDs, and loss rates react to the imposition of the LTV caps along the grid. The first three charts down the second column show their reaction to the DSTI caps. The chart in the lower left corner shows how much of the outstanding mortgage debt would be crowded out as a function of the LTV cap. It also shows the DSTI cap-implied loan volume reduction which is the loss rate equivalent to the LTV cap. Finally, the chart in the lower right corner shows an LTV cap DSTI cap mapping which also uses the loss rate equivalence concept. All calculations shown in Figures 2-8 assume that the caps are imposed on all historically granted mortgage loans (subsets of reference years could instead be chosen).

The loss rate equivalence concept deserves an explanation. It involves some additional calculation steps:

1. We impose the LTV caps and DSTI caps from the two grid vectors, $LTVgrid$ and $DSTIgrid$ both of size $Gx1$, to obtain vectors of EAD-weighted PDs, LGDs, loss rates (the element-wise product of the PD and LGD vectors) and volume reduction in percent of total EAD by the survey date for the population of households in a country. We refer to these vectors as $PD^{LTVcap/DSTIcap}$, $LGD^{LTVcap/DSTIcap}$, $LR^{LTVcap/DSTIcap}$ and $VOLred^{LTVcap/DSTIcap}$.

2. We estimate a second-order polynomial of the $DSTIgrid$ (LHS) on $LR^{DSTIcap}$ (RHS). We use the coefficients from this polynomial equation to then generate a vector of fitted DSTI caps conditional on LR^{LTVcap}. We thereby obtain estimates of DSTI caps that are needed to achieve the same loss rates that result from the imposition of the LTV caps (along their grid). We denote this loss rate-equivalent DSTI cap vector as $DSTIcap^{LTVcap-implied}$.

3. We estimate a second-order polynomial of $VOLred^{DSTIcap}$ on $DSTIgrid$. We use the coefficients from this polynomial equation to then generate a vector of fitted volume reduction estimates conditional on $DSTIcap^{LTVcap-implied}$ from the previous step. We thereby obtain a vector of volume reductions implied by the DSTI caps that are loss rate-equivalent to the initial LTV caps.

The results for Austria in Figure 2, for instance, show that the initial baseline PD of 1.7% starts falling from an LTV cap at about 70%, for the PD to fall to 1.2% at the left end of the LTV cap grid (50%). LGDs are more reactive, as they start falling from an LTV cap at 90% and then along a more negative slope toward lower LTV caps. The baseline LGD of 16.4% falls down to less than 4% under the 50% LTV cap. For the DSTI caps, the PD tends to be more reactive than with the LTV cap, falling to less than 0.2% under the 0.2 DSTI cap.

The volume reduction for Austria implied by the LTV caps shows that about 74% of the outstanding mortgage amounts would be crowded out if the LTV cap was imposed at 50%, opposed to about 22% at the cap of 120%. It can be seen that the loss rate-equivalent DSTI cap implies systematically less of a volume reduction, i.e. for a smaller share of the population the DSTI cap would have been binding to achieve the same loss rate as the corresponding LTV cap. The estimated mapping of the loss rate equivalent DSTI cap to the LTV cap suggests that for the extreme case of a 50% LTV cap, the DSTI cap equivalent would equal about 0.55. The loss rates for the two caps would be about equal at 0.03% (as they are loss rate-equivalent estimates). Yet in terms of volume reduction the two caps would imply the marked difference between 74% for the LTV cap opposed to 38% for the DSTI cap.

The findings across the seven countries can be summarised as follows: First, LTV caps have a stronger potential to reduce LGDs while DSTI caps have a stronger bearing on PDs; as expected because an LTV ratio is a stock ratio that is closely related to the LGD while DSTI ratios are related to flow variables (income and expense, the latter including debt service) and therefore to PDs. Both types of caps do, however, also reduce the respective other risk parameter through an apparent correlation of stock and flow characteristics at household-level. The cross-risk parameter response appears to be more pronounced for the DSTI cap which manages to compress also LGDs quite significantly.

To substantiate the latter point, Table 4 shows the estimates of two regressions, of the IDHBS model-implied PDs and LGDs upon the initial LTV, the DSTI, as well as the household member income-weighted average propensity of getting unemployed per household (using the household member-level propensities from Module B along with their income and/or unemployment benefit as observed as of the survey date). The estimates (focus on the normalised coefficients) confirm that the initial LTV ratio has a stronger effect on LGDs and the DSTI on PDs. The DSTI is insignificant in the LGD regression. The household-level weighted propensity of getting unemployed has a stronger and significant positive impact on PDs while it is smaller and insignificant in the LGD regression.

Second, the loss rate-equivalent volume reduction implied by the DSTI is systematically smaller than that of the LTV caps, which shall be due to their ability to compress both PDs and LGDs more symmetrically. In terms of macroeconomic feedback effects as a result of the policy-induced loan demand shock, the DSTI cap policy might be systematically and less detrimental for a given loss rate target that a policy maker would have in mind.

The model-implied PDs and LGDs also turn out to be correlated, with the cross-household correlation estimate equalling about 10% (pooled across all countries). A regression of the LGDs on PDs results in an intercept and slope estimate of 0.12 and 0.06, respectively, with both coefficients being significant at a 1% level and the R2 equalling 18% (without country fixed effects). PDs and LGDs are not related for structural reasons in the model, the reason being the aforementioned argument that there is little or no incentive for strategic default due to house price drops in full recourse systems, i.e. the predominant structure in European countries. If the model would be developed e.g. for the US, an explicit mechanism would need to be included in the default process that would account for strategic default incentives and therefore a link of PDs to house prices. The reason why PDs and LGDs nonetheless may correlate in full recourse systems through the cross-section is that households with higher PDs, i.e. those that tend to have higher DSTIs or unemployment propensities, tend to be also those with higher initial LTVs. The reason why PDs and LGDs would correlate through time is that macro fundamentals such as unemployment rates and income (driving PDs) correlate with house prices (driving LGDs) through the cycle.

3.2 Macroeconomic impact and feedback to household risk parameters

We start from an assumed LTV cap of 85% for all seven countries — for which the DSTI equivalent could be read from the charts in the lower left corners in Figures 2-8 — and simulate the macro feedback effects, involving the connection of Module E back to Module A for the inclusion of the policy-induced loan demand shock.

To identify the shock as a demand shock we constrain loan interest rates in the GVAR model to fall along with the volumes in the first quarter of the simulation in the country in which the policy shock originates. The year 2010 was taken as the reference year to compute the loan demand shocks relative to all outstanding loans implied by the LTV cap. The LTV cap-implied shocks for the seven countries (AT, BE, DE, LU, PT, SI and SK) amount to -2.3%, -3.4%, -0.9%, -1.0%, -0.5%, -2.3% and -1.2%. The shocks are further scaled downward by factors ranging from about 0.25 for Slovenia to 0.49 in Germany and Portugal (Table 2) to account for the share of household mortgage debt in total non-financial private sector debt. In parallel to the LTV cap-implied shocks we simulate the loss rate-equivalent DSTI shocks which are smaller compared to the LTV cap-implied volume shocks by a factor of about 0.7 on average across countries.

The responses (cumulative 1 year responses) of domestic macro variables from the seven simulations are summarised in Figure 9 for both the LTV cap-implied and loss rate-equivalent DSTI volume shocks. The cross-border responses are depicted in Figures 10 and 11. Along with the domestic responses (orange horizontal bars) which correspond to the first year effects in Figure 9, the figures show the median along with upper and lower quartiles across the 28 EU countries — excluding the country to which the policy shocks were applied. The cross-border effects can arise through two channels: first, the trade channel. Less credit provision in a country can dampen domestic real activity, including exports to and imports from other countries. Second, the locational credit measures, both in terms of volumes and prices, include credit that is provided to a country via subsidiaries, branches or direct cross-border lending from foreign banks. Cross-border effects can arise if a foreign bank's credit provision is being constrained by policy to country A, such that it would possibly divert its funds to country B (possibly its home country or other foreign countries).

Results in terms of household sector responses for PDs, LGDs, and loss rates are shown in Figures 12 and 13. After the first round mechanic impact of the imposition of the caps it can be seen again that there is a tendency for PDs to react more to a DSTI cap while LGDs are more responsive to LTV caps. Loss rates after the first round are equal, reflecting the loss rate-equivalence concept. Second round macro effects can then be seen to be of somewhat smaller magnitude across countries under the initial DSTI cap policy.

3.3 Impact on banks' capital position

Module F is used to now attach the baseline and policy-conditional risk parameters to the household mortgage portfolios of 49 SSM banks from six of the seven countries for which results were presented thus far; excluding banks from Slovakia as data was insufficient, see Table 5 for the list of banks that are included. The same 1-year horizon is still adopted. The LTV and DSTI cap-implied responses, once excluding and once including macro feedback effects, are shown in Figure 14. The results for the sample of banks are pooled and anonymised.

The results suggest that the median CET1 response amounts to 0.08 percentage points, a rather limited effect. There is a number of banks for which the impact is stronger, however, exceeding 20 basis points and moving up to 0.9 percentage points. The reason for the responses to be rather small is that we shock only the mortgage loan portfolios of the banks. Moreover, the simulation horizon is set to only 4 quarters.

4 Conclusions

The purpose of the paper was to develop an integrated micro-macro model that can be used to assess the responsiveness of household sector risk parameters, i.e. probabilities of default and loss given default, to lending standard-related macroprudential policy measures. Short-term macroeconomic feedback effects can be quantified to assess the second-round impact on the household risk parameters.

Our simulation results for seven European countries suggest that both LTV and DSTI caps can help reduce PDs and LGDs and hence loss rates for the household sector, while macro feedback effects may in the short-term, however, offset to some extent the initial and otherwise unambiguously positive effect. The counteracting dampening effect is due to the policy-induced loan demand shock which has the potential to drag economic activity and curb house price growth to an extent, with the latter in fact being a desired outcome of borrower-based macroprudential policy.

The simulation results suggest that households with higher initial LTV ratios are systematically those who are less able to service their debt. That is, PDs (not only LGDs) fall in response to LTV caps, which is not a necessity as LTV ratios are related to leverage of a household balance sheet (i.e. to stock measures) and should for that reason primarily exert their impact through LGDs. Thus, the fact that also PDs fall in response to the imposition of LTV caps means that leverage and the ability to meet periodic debt repayment obligations correlate empirically. Likewise for the opposite case: LGDs fall after imposing a DSTI cap despite its primary impact going via PDs. In fact the latter cross-parameter effect for DSTI caps appears to dominate. Hence, DSTI caps can be more effective than LTV caps in the sense that a certain reduction in household sector loss rates that a policy maker wishes to achieve can be accomplished with a lower reduction in loan volumes when considering the DSTI cap-based policy. Irrespective of the imposition of LTV or DSTI caps, the results suggest that PDs and LGDs correlate empirically in the cross-section of households despite the fact that there are no structural reasons for that, as house price drops do not imply incentives for strategic default in full recourse systems, which is the predominant structure in European countries. The correlation stems from a positive correlation of DSTIs and LTVs in the cross-section.

Three extensions to the model are envisaged: first, population growth can be made dynamic. The current version of the model operates with a static population. Second, the loan supply process shall be made endogenous, for households that do not have a mortgage loan at the outset to be allowed to apply for and be granted a mortgage loan. Third, an explicit distinction between principal and interest payments can be introduced to make repayment a function of the interest rate development in the scenario, including the second round deviations, which is relevant in particular in countries with variable rate regimes. The first two extensions shall help allow for a longer assessment horizon which we currently advise to set to no more than 2 years, as otherwise the results might be dominated by survivor bias, i.e. PDs fall because high risk households default on their debt repayment early during the simulation horizon. Careful attention should then, however, be given to finding the right balance between additional model complexity by introducing dynamic population or loan origination features as opposed to a simpler, as the current, model structure for the sake of robustness.

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Annex A: Details — Module A (GVAR)

The GVAR model that we set up for Module A comprises $i = 1, ..., N$ countries from the EU ($N = 28$). The endogenous variables are collected in a $k_i \times 1$ vector $\mathbf{y}_{it}$ which is related to a number of autoregressive lags up to P and a $k_i^* \times 1$ vector of foreign variables $\mathbf{y}_{it}^*$ that enters the model time-contemporaneously and with a number of lags up to Q, that is,

$$\mathbf{y}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \sum_{p=1}^{P} \mathbf{\Phi}_{ip}\mathbf{y}_{i,t-p} + \sum_{q=0}^{Q} \mathbf{\Lambda}_{iq}\mathbf{y}_{i,t-q}^* + \mathbf{\Psi}\mathbf{d}_t + \epsilon_{it} \tag{15}$$

where $\mathbf{a}_{i0}$, $\mathbf{a}_{i1}$, $\mathbf{\Phi}_{ip}$, $\mathbf{\Lambda}_{iq}$, and $\mathbf{\Psi}$ are coefficient matrices of size $k_i \times 1$, $k_i \times 1$, $k_i \times k_i$, $k_i \times k_i^*$, and $d_i \times 1$ respectively. The vector $\mathbf{d}_t$ may contain global exogenous variables (which are not included for the application presented here). It is assumed that ϵ_{it} is i.i.d. with zero mean and covariance matrix $\mathbf{\Sigma}_{ii}$.

The endogenous variables contained in the model include: Unemployment rates, long-term interest rates (10-year benchmark government bond yields), stock price indices, nominal compensation per employee, residential property price indices, nominal GDP, GDP deflator, short-term interest rates (3-month money market interest rates), domestic credit from financial institutions to the private sector as well as nominal loan interest rates. Loan volumes are sourced from the ECB's BSI statistics. Loan interest rates are sourced from the ECB's MIR statistics. The loan volume and price variables have a locational definition, i.e. refer to credit that is supplied from banks (whether domestic or via foreign branches, subsidiaries or direct cross-border lending) to the resident households and non-financial corporations of a country. For all variables, except loan volumes and loan interest rates, a trade weighting scheme is employed.[25] For loan volumes and loan interest rates, a unit weighting scheme is employed, which means that domestic macro variables are allowed to be influenced only by their corresponding domestic credit volumes and prices. Vice versa, also the credit volumes and prices are allowed to be driven only by their domestic macro variables. The rationale for assuming this structure is that the credit volume and price variables have a locational definition, i.e. there should be no direct channel for foreign macro conditions to drive domestic credit conditions. Spillover effects in either direction can of course well arise through indirect channels.

Solving for the global model follows the standard procedure whereby local models need to be properly reformatted and stacked, involving the weights. The description of how to solve the global model will in the following be brief. For details that are omitted we refer to Pesaran et al. (2004).

A country-specific $(k_i + k_i^*) \times 1$ vector $\mathbf{z}_{it}$ is defined as follows.

$$\mathbf{z}_{it} = \begin{bmatrix} \mathbf{y}_{it} \\ \mathbf{y}_{it}^* \end{bmatrix} \tag{16}$$

[25] Trade statistics are retrieved from the IMF DOTS database.

The local models in equation 15 can then be reformulated.

$$\mathbf{A}_{0i}\mathbf{z}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{A}_{1i}\mathbf{z}_{i,t-1} + ... + \mathbf{A}_{Pi}\mathbf{z}_{i,t-P} + \epsilon_{it} \tag{17}$$

where it is assumed for ease of notation in the following that $P = Q$ and the global exogenous variable vector $\mathbf{d}_t$ be empty. The $\mathbf{A}_{ip}$ coefficient matrices are all of size $k_i \times (k_i + k_i^*)$ and have the following form.

$$\begin{aligned} \mathbf{A}_{i0} &= (\mathbf{I}_{k_i}, -\mathbf{\Lambda}_{i0}) \\ \mathbf{A}_{i1} &= (\mathbf{\Phi}_{i1}, \mathbf{\Lambda}_{i1}) \\ &... \\ \mathbf{A}_{iP} &= (\mathbf{\Phi}_{iP}, \mathbf{\Lambda}_{iP}) \end{aligned} \tag{18}$$

The endogenous variables across items in the cross-section are stacked in one global vector $\mathbf{y}_t$ which is of size $k \times 1$ where $k = \sum_{i=1}^{N} k_i$. Here, we need to map the local variable vectors $\mathbf{z}_{it}$ to the global endogenous variable vector $\mathbf{y}_t$ which is accomplished via $(k_i \times k_i^*) \times k$ link matrices $\mathbf{W}_i$. With $\mathbf{z}_{it} = \mathbf{W}_i\mathbf{y}_t$ we can rewrite the model once more.

$$\mathbf{A}_{i0}\mathbf{W}_i\mathbf{y}_t = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{A}_{i1}\mathbf{W}_i\mathbf{y}_{t-1} + ... + \mathbf{A}_{iP}\mathbf{W}_i\mathbf{y}_{t-P} + \epsilon_{it} \tag{19}$$

Now, we move from item-specific models to the global model by stacking the former in one global system, that is,

$$\mathbf{G}_0\mathbf{y}_t = \mathbf{a}_0 + \mathbf{a}_1t + \mathbf{G}_1\mathbf{y}_{t-1} + ... + \mathbf{G}_P\mathbf{y}_{t-P} + \epsilon_t \tag{20}$$

where the $\mathbf{G}_{0,...,P}$ matrices are of size $k \times k$ and have the following form.

$$(\mathbf{G}_0, ..., \mathbf{G}_P) = \begin{pmatrix} \mathbf{A}_{01}\mathbf{W}_1 & & \mathbf{A}_{P1}\mathbf{W}_1 \\ \mathbf{A}_{02}\mathbf{W}_2 & , ..., & \mathbf{A}_{P2}\mathbf{W}_2 \\ ... & & ... \\ \mathbf{A}_{0N}\mathbf{W}_N & & \mathbf{A}_{PN}\mathbf{W}_N \end{pmatrix} \tag{21}$$

A reduced form of the global model is finally obtained by pre-multiplying the system with the inverse of $\mathbf{G}_0$. This representation is observationally equivalent to the model in equation 15 and can now be used for forecasting and impulse response analysis.

$$\mathbf{y}_t = \mathbf{G}_0^{-1}\mathbf{a}_0 + \mathbf{G}_0^{-1}\mathbf{a}_1t + \mathbf{G}_0^{-1}\mathbf{G}_1\mathbf{y}_{t-1} + ... + \mathbf{G}_0^{-1}\mathbf{G}_P\mathbf{y}_{t-P} + \mathbf{G}_0^{-1}\epsilon_t \tag{22}$$

The shock simulations that are conducted with the model, specifically when using Module E to initiate a counterfactual policy simulation, make use of a sign restriction methodology.[26] The shocks are applied to the locational credit variable, with sign restrictions being imposed on the loan interest rate variable for the first quarter of the simulation in the same country. In order to identify the impulses to loan volumes as a credit demand shock, prices are assumed to fall on impact along with loan volumes.

Annex B: Details — Module B (Logistic model for employment status)

The logistic model is defined for the individual household members for all countries, with the dependent variable indicating that household members are employed. The model estimates for the seven countries for which we present simulation results in the paper are summarised in Table B.1.[27]

For the marital status variable, the indicator denotes 'single', hence the estimates suggest that being married systematically increases the probability of being employed in all countries. The education variable is coded such that the dummy indicates 'no university degree', thus a university degree increases the probability of getting employed. Concerning the gender variable, the signs of the coefficients across countries switch at times and are in 4 out of the 7 countries not significant. The dummy equals 1 for males, i.e. females appear to have a somewhat higher propensity of being employed in Belgium, Portugal and Slovakia. The domestic/foreign variable is coded such that the dummy indicates 'foreign', hence all across countries the estimates suggest that foreigners are less likely to be employed.

The receiver operating curves for the seven countries are collected in Figure B.1.

[26] For a useful entry point to the literature related to sign restricted SVARs see Faust (1998), Canova and Nicolo (2002), and Uhlig (2005).

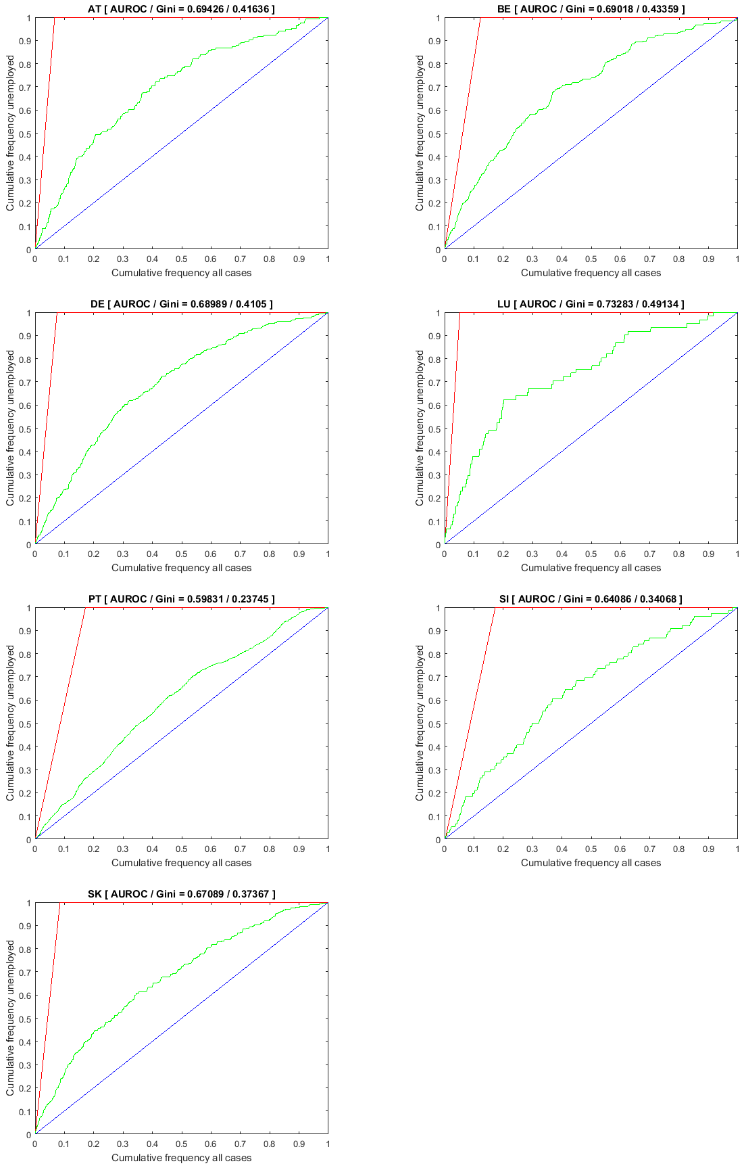
[27] The number of observations (household members) is larger for all countries than indicated in the right part of Table 4 for the reduced population that has mortgage debt outstanding, because the logistic model is estimated on the extended population including also those household members that do not have mortgage debt outstanding. Yet, the number of household members is somewhat smaller than indicated in the left part of Table 4, the total population, because the predictor variables included in the logistic model are not observed for some household members.

Table B.1: Logistic model estimates

	AT	BE	DE	LU	PT	SI	SK
Intercept	4.98 (0.00)	2.99 (0.00)	4.65 (0.00)	1.85 (0.01)	2.40 (0.00)	3.26 (0.00)	2.66 (0.00)
Marital status	-1.22 (0.00)	-0.83 (0.00)	-1.12 (0.00)	-0.62 (0.04)	-0.56 (0.00)	-1.21 (0.00)	-0.70 (0.00)
Education	-0.98 (0.00)	-1.24 (0.00)	-1.15 (0.00)	-0.63 (0.04)	-1.06 (0.00)	-0.66 (0.05)	-1.22 (0.00)
Gender	-0.03 (0.85)	0.27 (0.04)	-0.08 (0.54)	0.11 (0.69)	0.33 (0.00)	0.21 (0.43)	0.25 (0.06)
Dom/Foreign	-1.32 (0.00)	-1.08 (0.00)	-0.69 (0.00)	-0.96 (0.00)	-0.16 (0.19)	-0.10 (0.84)	1.00 (0.33)
Age	-0.02 (0.03)	0.00 (0.63)	-0.02 (0.00)	0.06 (0.00)	0.00 (0.23)	-0.02 (0.14)	0.03 (0.00)
Obs	2,497	2,362	3,957	1,186	5,175	445	3,176
AUROC	0.69	0.69	0.69	0.73	0.6	0.64	0.67
Gini	0.42	0.43	0.41	0.49	0.24	0.34	0.37

Note: The table reports the coefficient estimates (including p-values in parentheses) from a logistic regression whose dependent variable equals 1 for household members that are employed. AUROC denotes the estimate of the area under the receiver operating curve.

Figure B.1: Receiver operating characteristic (ROC) curves of the logistic models for the employment status



Note: The figure shows the receiver operating characteristic (ROC) curves (in green) for all seven countries for which simulation results are presented in the paper. Along with the ROC curves, the 45-degree line is added in blue (reflecting the random scoring), and the observed/empirical cumulative frequency of being unemployed in red (reflecting the optimal scoring).

Annex C: Charts and tables

Table 1: Micro data from the Household Survey as input to the IDHBS model

Category	Variable	Variable name (long)	Role in the model
Household-level, asset side	DA1110	Current value of household's main residence	For calculating current value and forward path of LGDs in Module D
	DA2103	Current market value of bonds	Quantify market value of bonds (sovereign, corporate), i.e. B in eq. (7)
	DA2105	Current market value of stocks	Quantify market value of shares, i.e. S in eq. (7)
	DA2100	Total financial assets	Remainder of liquid fin. assets after subtracting bonds+stocks; C in eq. (7)
Household-level, liability side	DL1100	Outstanding balance of mortgage debt	Quantify outstanding debt; L in eq. (7)
Household-level, flows	DL2100	Monthly payments to repay outst. mortgages	To quantify the periodic repayment (expense) for eq. (7)
Household member-level, flows	PG0110	Annual gross income	Calibrate amount of periodic income for empl. HMs in eq. (7)
	PG0510	Annual gross unemployment benefit	Calibrate amount of periodic income for unempl. HMs in eq. (7)
Other household member-level	PE0100a	Labour status	Basis for left hand-side variable in Module B
	PA0100	Marital status	Control variables in the logistic model for the unempl. status (Module B)
	PA0200	Level of education	Control variables in the logistic model for the unempl. status (Module B)
	RA0300	Age	Control variables in the logistic model for the unempl. status (Module B)
	RA0200	Gender	Control variables in the logistic model for the unempl. status (Module B)
	SA0100	Residence indicator (for both HHs and HMs)	Required to group household members in countries
	ID	Household member ID	Required to identify HMs and track their assignment to HHs
Other household-level	HB0700	Initial year of mortgage	Required in Module E
	HB0800	Initial value of the house	Required to compute initial LTV ratio
	HB140x	Initial amounts owed	Required to compute initial LTV ratio
	HB0500	% of ownership	Required to compute initial LTV ratio
	IniLTV	Initial LTV, sum(HB140X)/(HB0500*HB0800)	Required for counterfactual policy simulations in Module E
	CurrDSTI	Current DSTI, (3*DL1100)/(0.25*PG0110)	Required for counterfactual policy simulations in Module E
	SA0010	Household ID	To identify HHs (not unique across countries; made unique in model)

Note: The table summarises the variables that are taken from the Eurosystem Household Finance and Consumption Survey as input for the IDHBS model. The variable codes reported in the second column of the table are aligned with the codes from the household survey. HM abbreviates 'household member'. HH abbreviates 'household'. See Section 2 for details.

Table 2: Metadata parameters for the calibration of the IDHBS model

	AT	BE	CY	DE	ES	FI	FR	GR	IT	LU	MT	NL	PT	SI	SK
Duration of unemployment in quarters	2.69	2.69	5.08	2.69	2.69	3.30	2.69	2.69	2.69	2.69	5.08	2.69	2.69	5.08	10.56
Cost of living relative to periodic gross income	0.87	0.85	0.91	0.84	0.88	0.92	0.85	0.99	0.89	0.81	0.92	0.87	0.93	0.87	0.91
Income tax rate	0.40	0.42	0.26	0.39	0.32	0.40	0.41	0.30	0.43	0.32	0.20	0.36	0.23	0.35	0.31
Net replacement rate	0.33	0.50	0.43	0.36	0.54	0.34	0.41	0.32	0.39	0.57	0.31	0.49	0.58	0.55	0.43
Mortgage loans relative to total private sector loans	0.32	0.46	0.29	0.49	0.48	0.52	0.45	0.36	0.29	0.32	0.40	0.50	0.49	0.25	0.45

Note: The table reports the data that are needed to calibrate various meta parameters of the IDHBS model. All parameters are based on 2013 data. The duration of unemployment parameter has — in the absence of sufficiently granular country level data — for most countries set to the G7 weighted average (2.69). See Section 3 for further details.

Table 3: Micro data, household and household member count

	Total population in survey			Population for which mortgage outstanding and initial LTV available		
	Households (HHs)	Household members (HMs)	HM/HH	Households (HHs)	Household members (HMs)	HM/HH
Austria	2,380	5,014	2.1	384	1,127	2.9
Belgium	2,327	5,516	2.4	655	2,070	3.2
Germany	3,565	8,134	2.3	812	2,332	2.9
Luxembourg	950	2,540	2.7	328	1,036	3.2
Portugal	4,404	11,126	2.5	1,016	3,082	3.0
Slovenia	343	964	2.8	31	106	3.4
Slovakia	2,017	5,351	2.7	229	705	3.1
Total	**15,986**	**38,645**	**2.4**	**3,455**	**10,458**	**3.0**

Note: The table summarises the number of households and household members for the seven countries for which illustrative simulation results are presented in Section 3.

Table 4: The role of initial LTV versus DSTI in driving PDs and LGDs

PD	Coef	Coef*	*p*
LTVini	7.581	0.098	0
DSTI	0.264	0.034	0.025
PURX	1.077	0.176	0
No. of obs.	3,455	R2	0.144

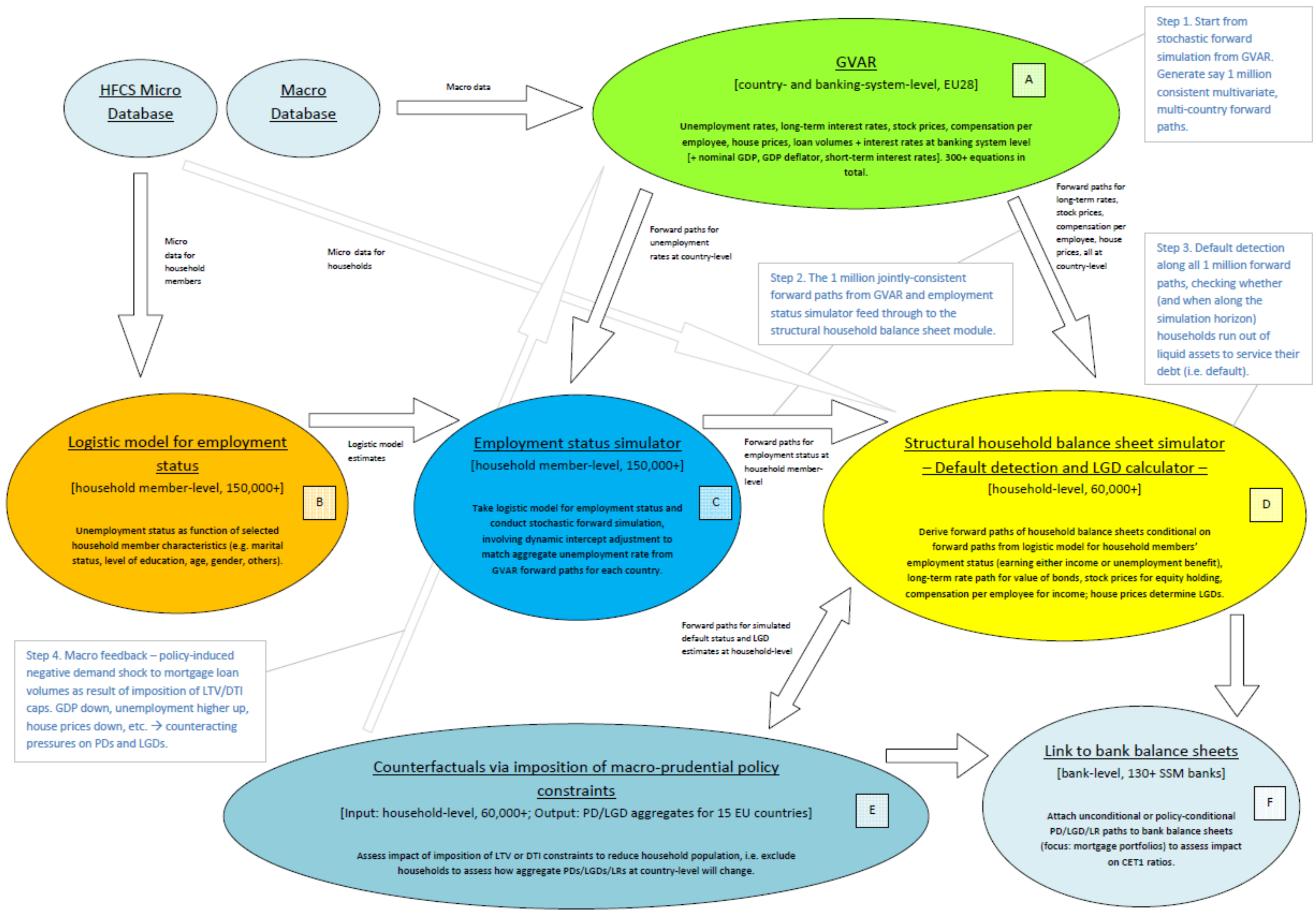
LGD	Coef	Coef*	*p*
LTVini	2.441	0.136	0
DSTI	-0.001	-0.02	0.96
PURX	0.021	0.017	0.672
No. of obs.	3,455	R2	0.14

Note: The regression estimates presented in these two tables are based on the IDHBS model-implied PDs (left) and LGDs (right) for the households from the subset of seven countries that are subject to the analysis. It is the subset of households that have mortgage debt outstanding. $Coef*$ denotes the normalised coefficients which are obtained by multiplying the initial coefficients with the ratio of the standard deviations of the right hand-side over that of the left hand-side variable. The variable $PURX$ is a household member-income weighted average propensity of being unemployed for each household. The underlying household member-level propensities are the output from Module B.

Table 5: SSM banks included in the simulation (for Module F)

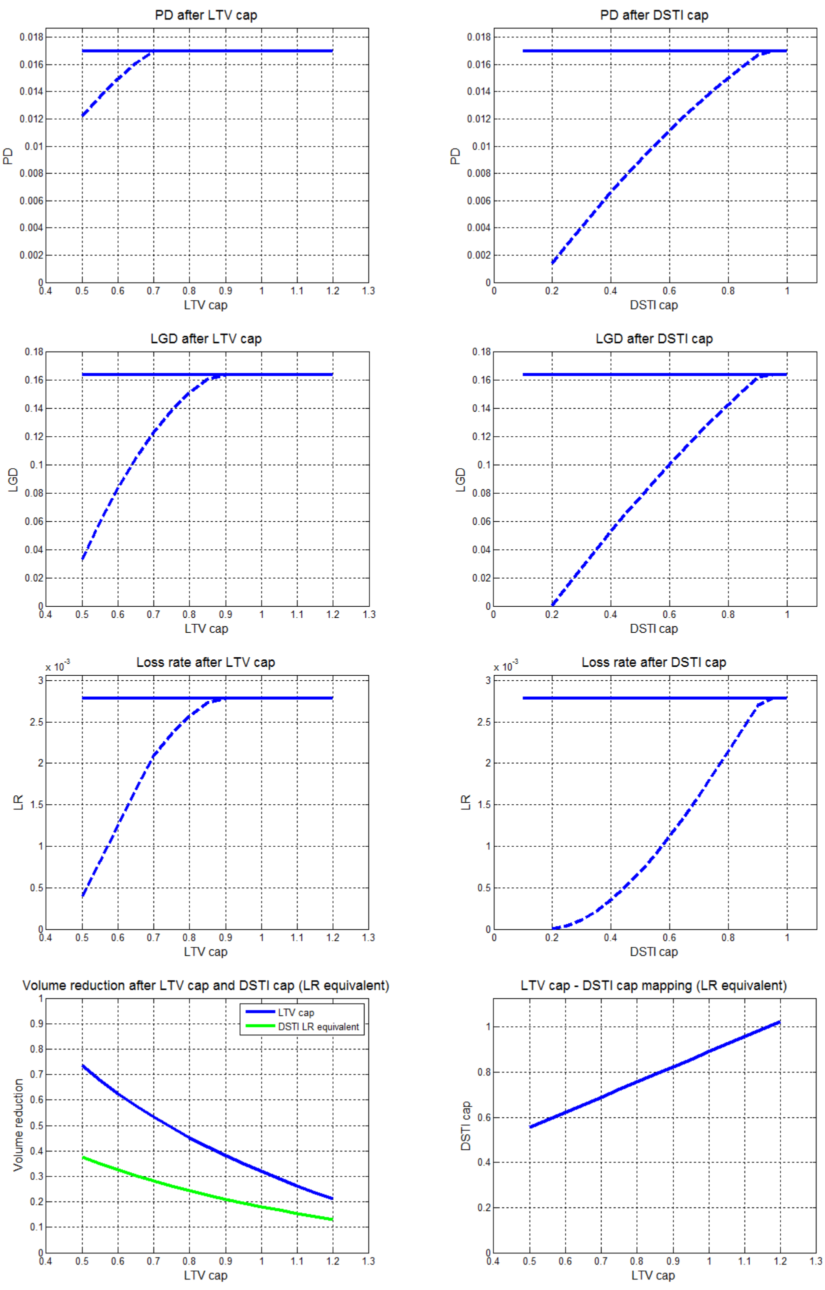
#	Location	Bank ID	Bank name
1	Austria	ATBAWA	BAWAG P.S.K. Bank fr Arbeit und Wirtschaft und Oest. Postsparkasse AG
2		ATERST	Erste Group Bank AG
3		ATRANI	Raiffeisenlandesbank Niederoesterreich-Wien AG
4		ATRAOB	Raiffeisenlandesbank Oberoesterreich AG
5		ATRAZE	Raiffeisen Zentralbank Oesterreich AG
6		ATVBH	Oesterreichische Volksbanken-AG
7	Belgium	BEABIG	Argenta Bank- en Verzekeringsgroep
8		BEAXA	AXA Bank Europe SA
9		BEBELF	Belfius Banque SA
10		BEBNY	The Bank of New York Mellon SA
11		BEDXIA	Dexia NV
12		BEKBC	KBC Group NV
13	Germany	DEAAB	Aareal Bank AG
14		DEAPAE	Deutsche Apotheker- und rztebank eG
15		DEBLB	Bayerische Landesbank
16		DEBSW	Wuestenrot Bausparkasse AG
17		DECOMM	Commerzbank AG
18		DEDEBK	Deutsche Bank AG
19		DEDEKA	DekaBank Deutsche Girozentrale
20		DEDZB	DZ Bank AG Deutsche Zentral-Genossenschaftsbank
21		DEHASP	HASPA Finanzholding
22		DEHSH	HSH Nordbank AG
23		DEHYMU	Muenchener Hypothekenbank eG
24		DEHYRE	Hypo Real Estate Holding AG
25		DEIKB	IKB Deutsche Industriebank AG
26		DEKFW	KfW IPEX-Bank GmbH
27		DELBB	Landesbank Berlin Holding AG
28		DELBW	Landesbank Baden-Wuerttemberg
29		DELHTG	Landesbank Hessen-Thueringen Girozentrale
30		DELKBW	Landeskreditbank Baden-Wuerttemberg-Foerderbank
31		DELWREB	Landwirtschaftliche Rentenbank
32		DENLG	Norddeutsche Landesbank-Girozentrale
33		DENRW	NRW.Bank
34		DESEB	SEB AG
35		DEVWFS	Volkswagen Financial Services AG
36		DEWBP	Wuestenrot Bank AG Pfandbriefbank
37		DEWGZ	WGZ Bank AG Westdeutsche Genossenschafts-Zentralbank
38	Luxembourg	LUBCEE	Banque et Caisse d'Epargne de l'Etat, Luxembourg
39		LUCLST	Clearstream Banking S.A.
40		LUPCAP	Precision Capital S.A.
41		LURBC	RBC Investor Services Bank S.A.
42		LUSTST	State Street Bank Luxembourg S.A.
43		LUUBS	UBS (Luxembourg) S.A.
44	Portugal	PTBCP	Banco Comercial Portugues, SA
45		PTBPI	Banco BPI, SA
46		PTCGD	Caixa Geral de Depositos, SA
47	Slovenia	SINKBM	Nova Kreditna Banka Maribor d.d.
48		SINLB	Nova Ljubljanska Banka d. d., Ljubljana
49		SISID	SID - Slovenska Izvozna in Razvojna Banka, d.d., Ljubljana

Figure 1: Structure of the IDHBS model



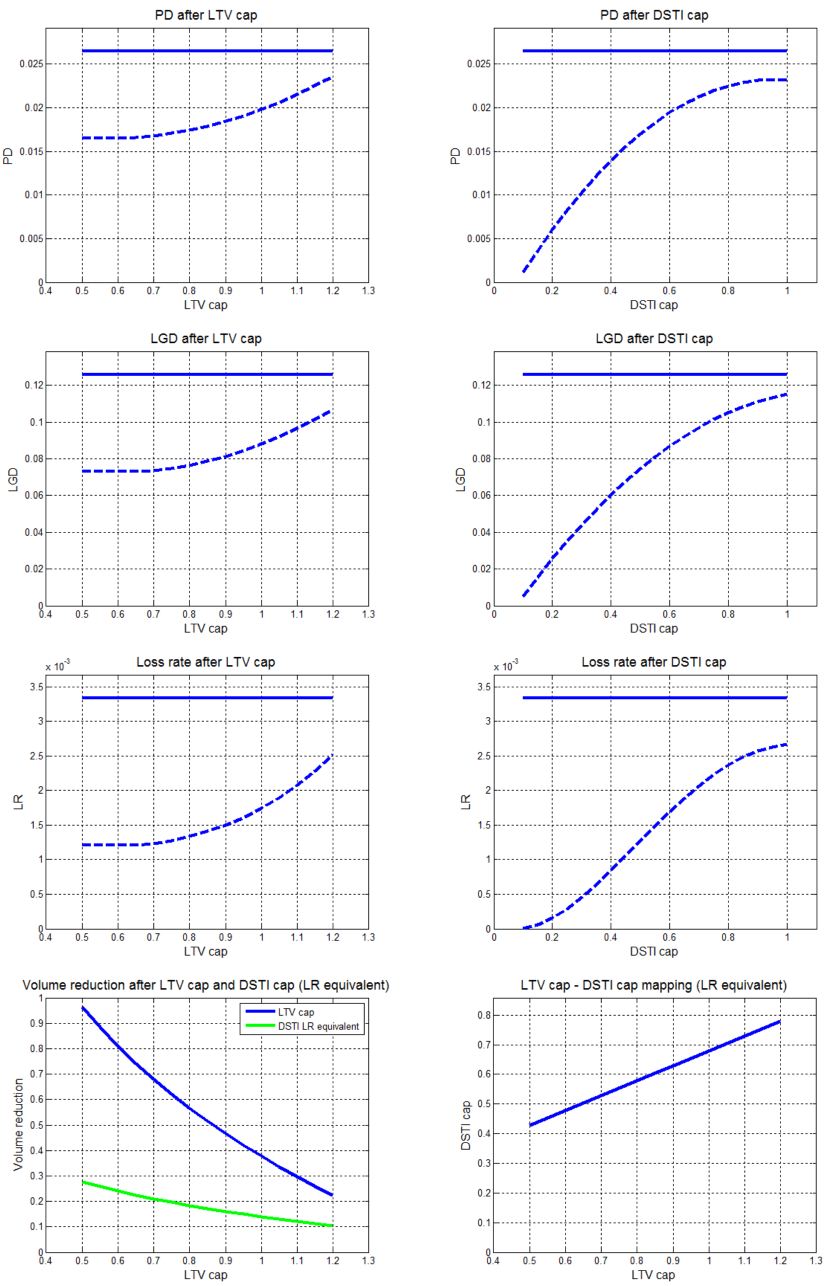
Note: The schematic overview shows the structure of the IDHBS model, which contains two database inputs and six core modules (A-F). See Section 2 for details.

Figure 2: LTV vs DSTI impact assessment — Austria



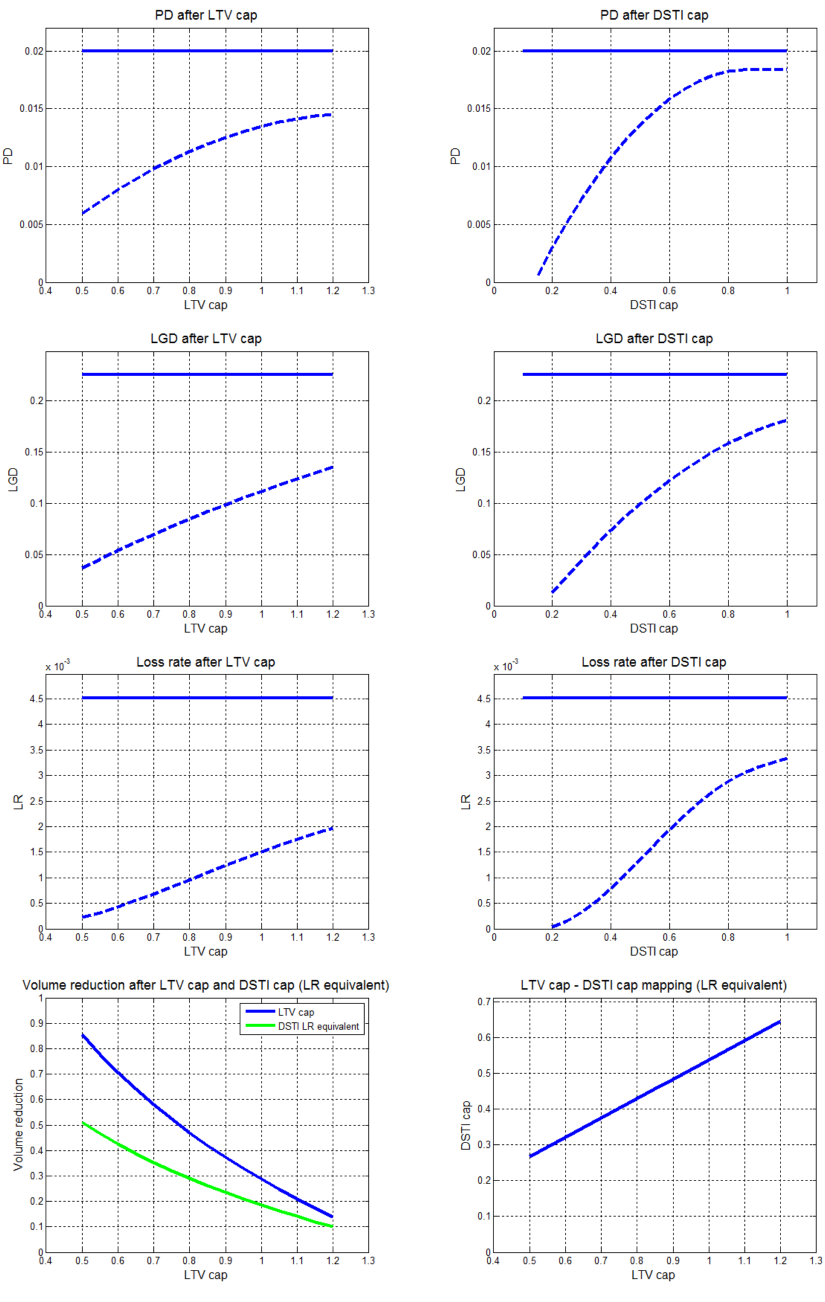
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 3: LTV vs DSTI impact assessment — Belgium



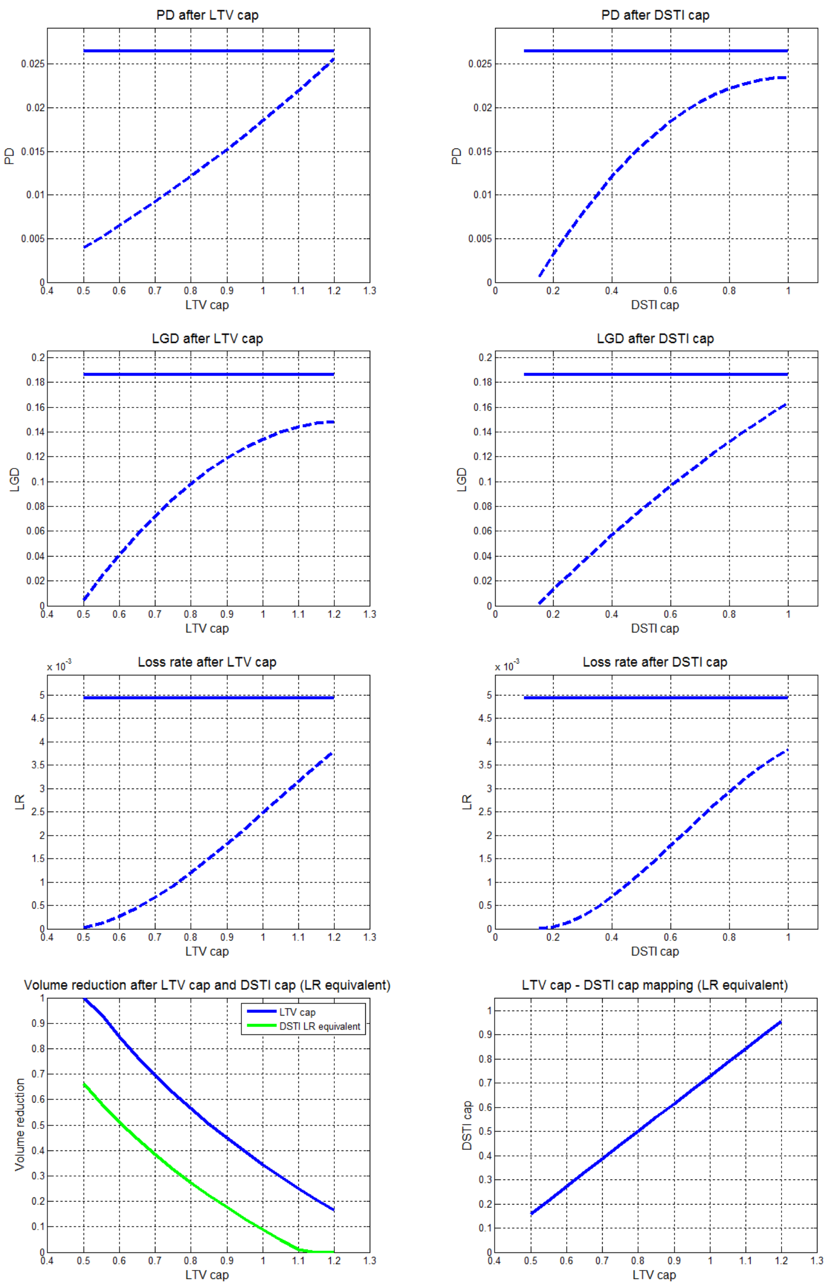
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 4: LTV vs DSTI impact assessment — Germany



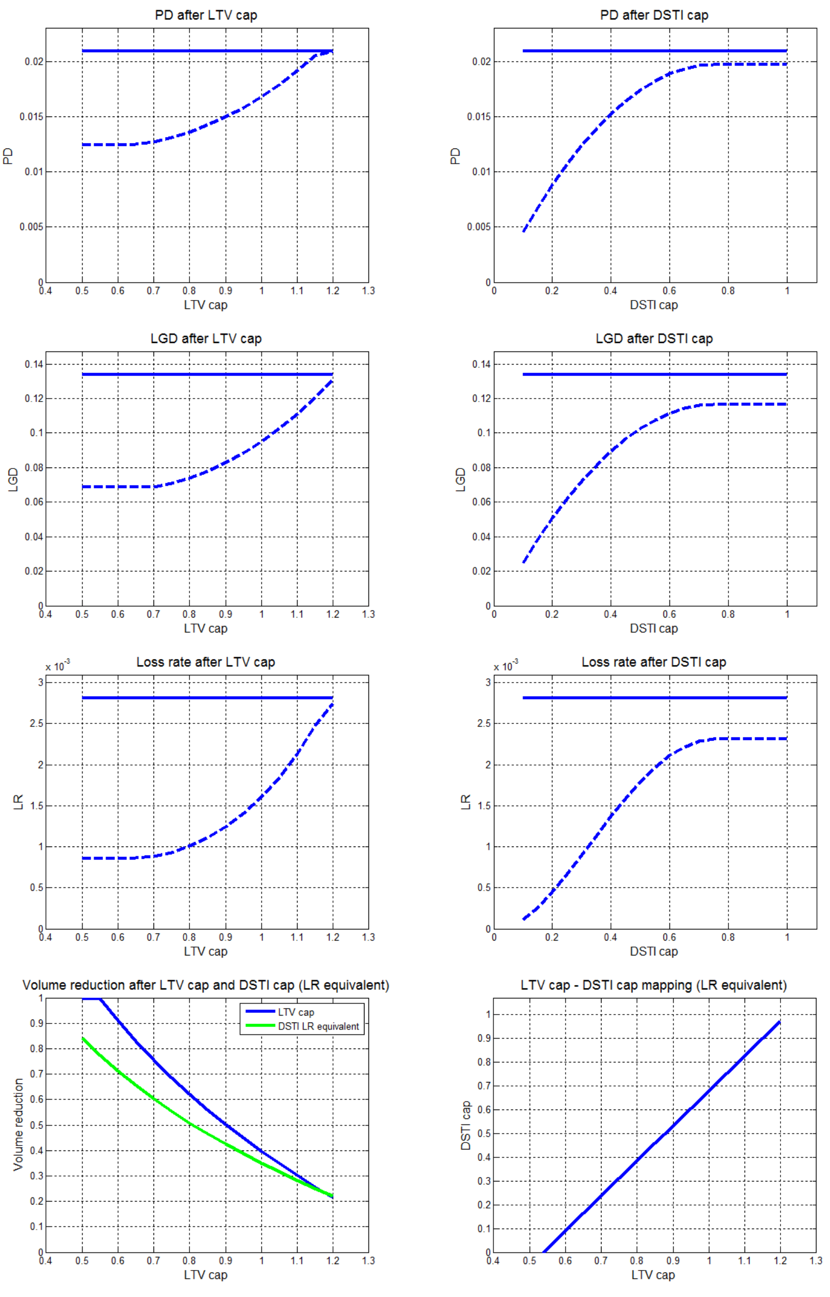
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 5: LTV vs DSTI impact assessment — Luxembourg



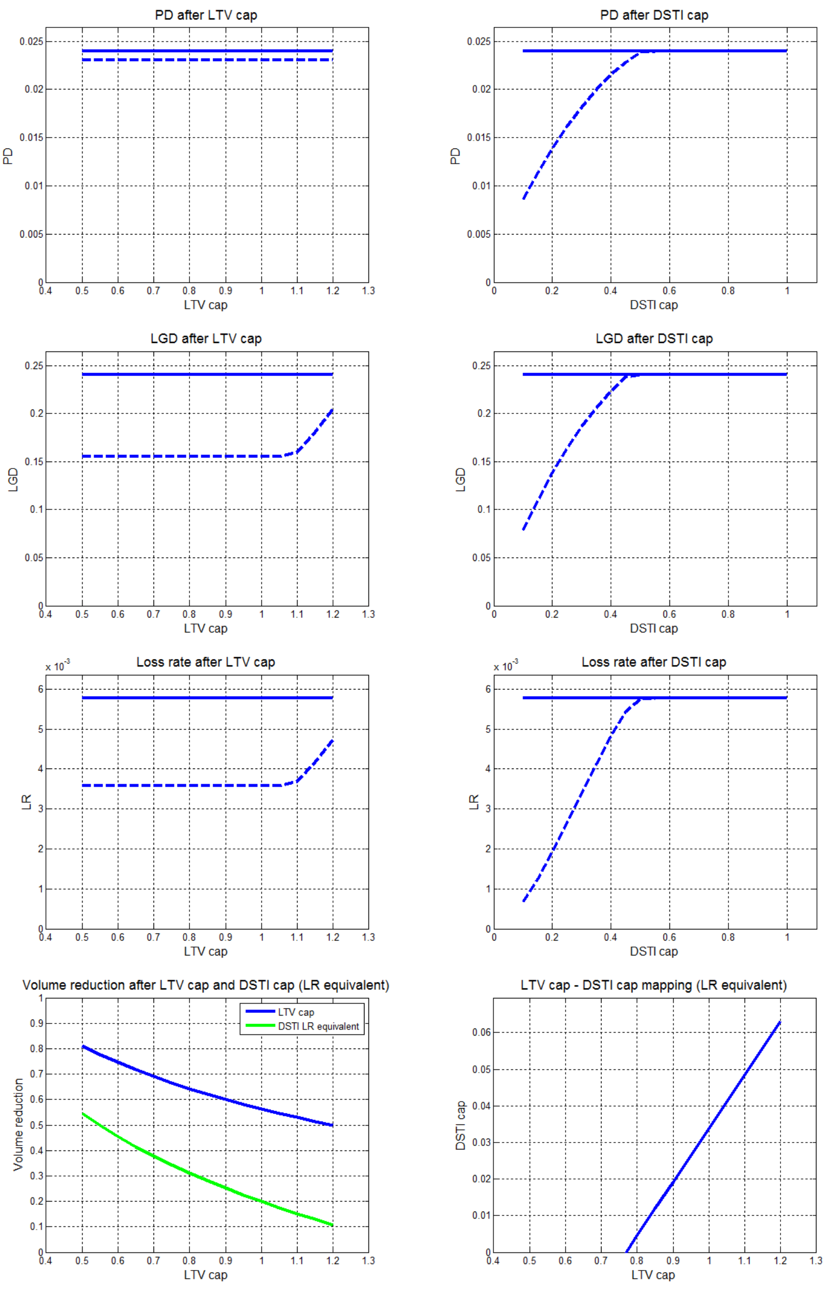
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 6: LTV vs DSTI impact assessment — Portugal



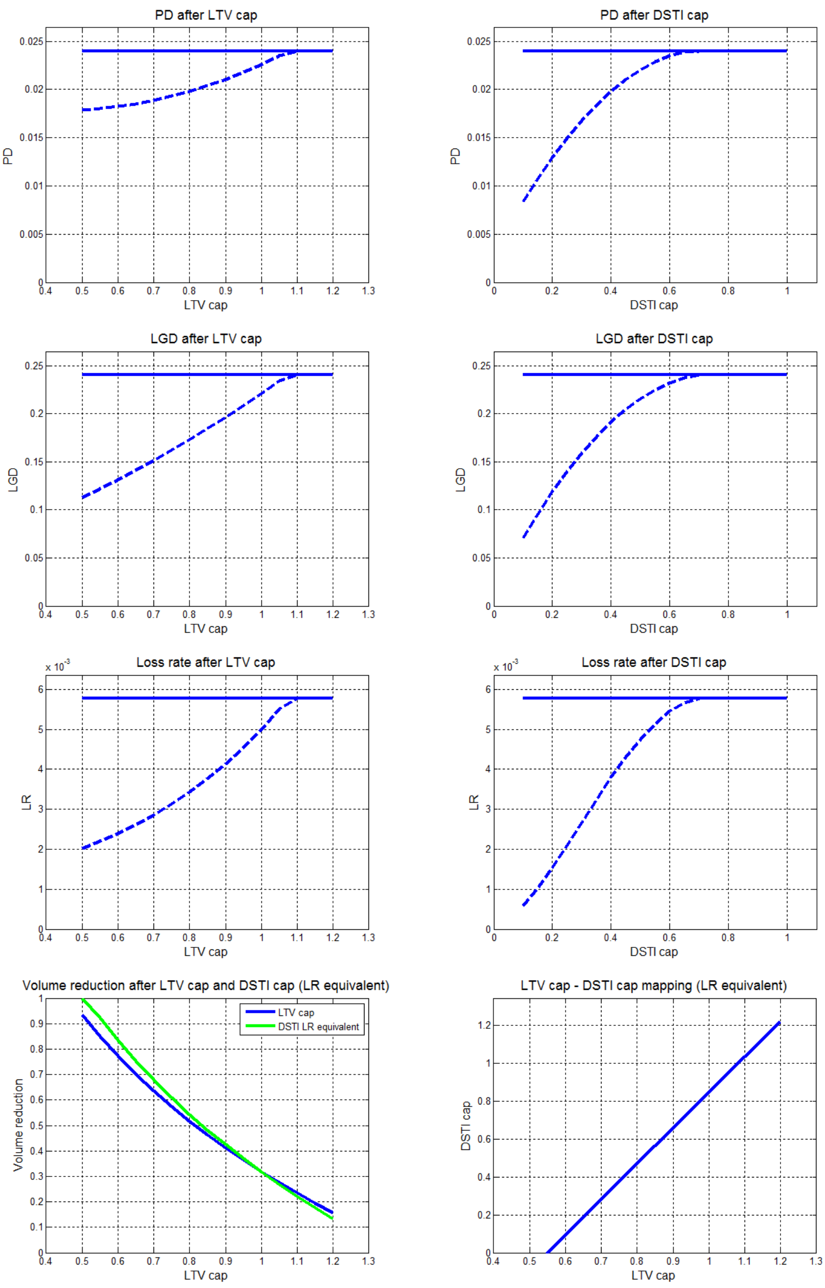
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 7: LTV vs DSTI impact assessment — Slovenia



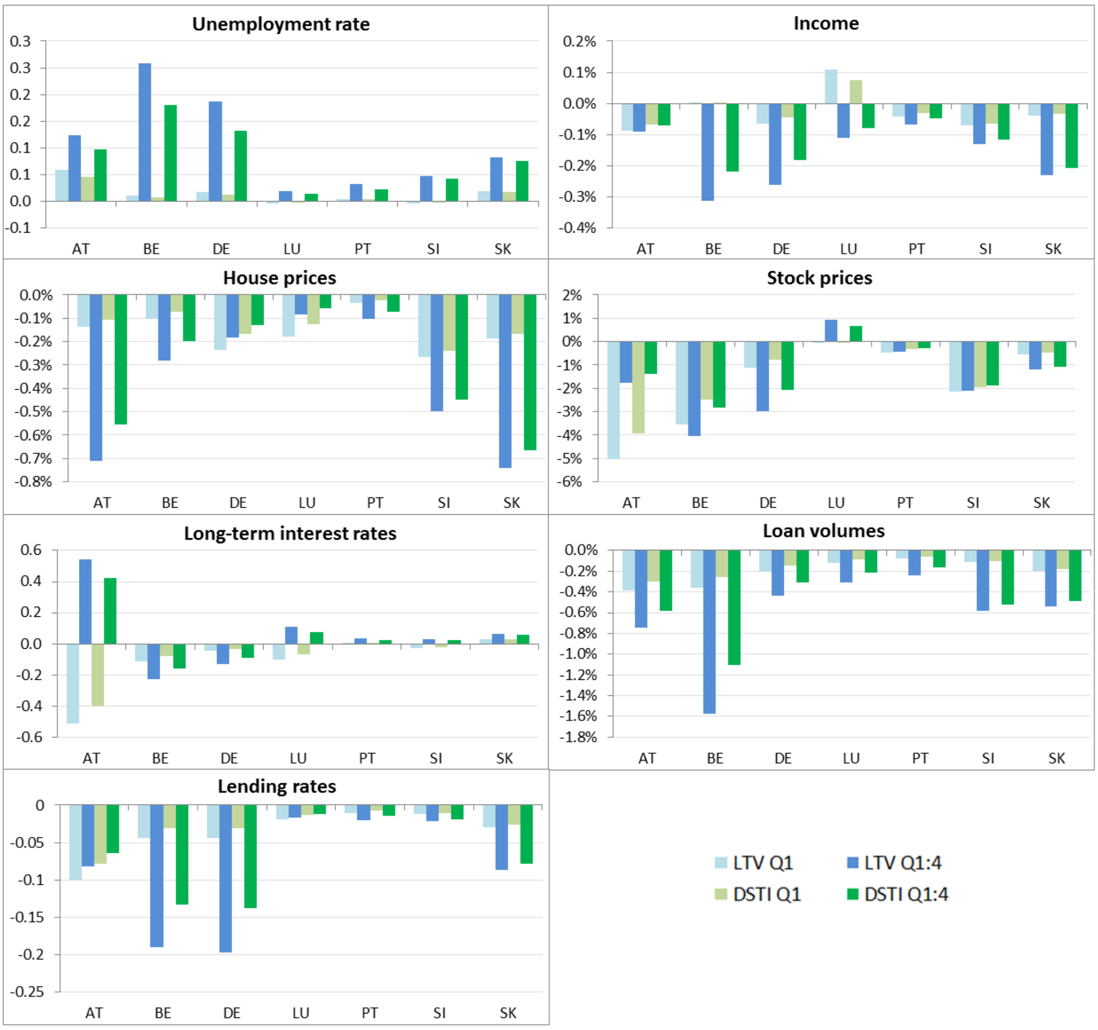
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 8: LTV vs DSTI impact assessment — Slovakia



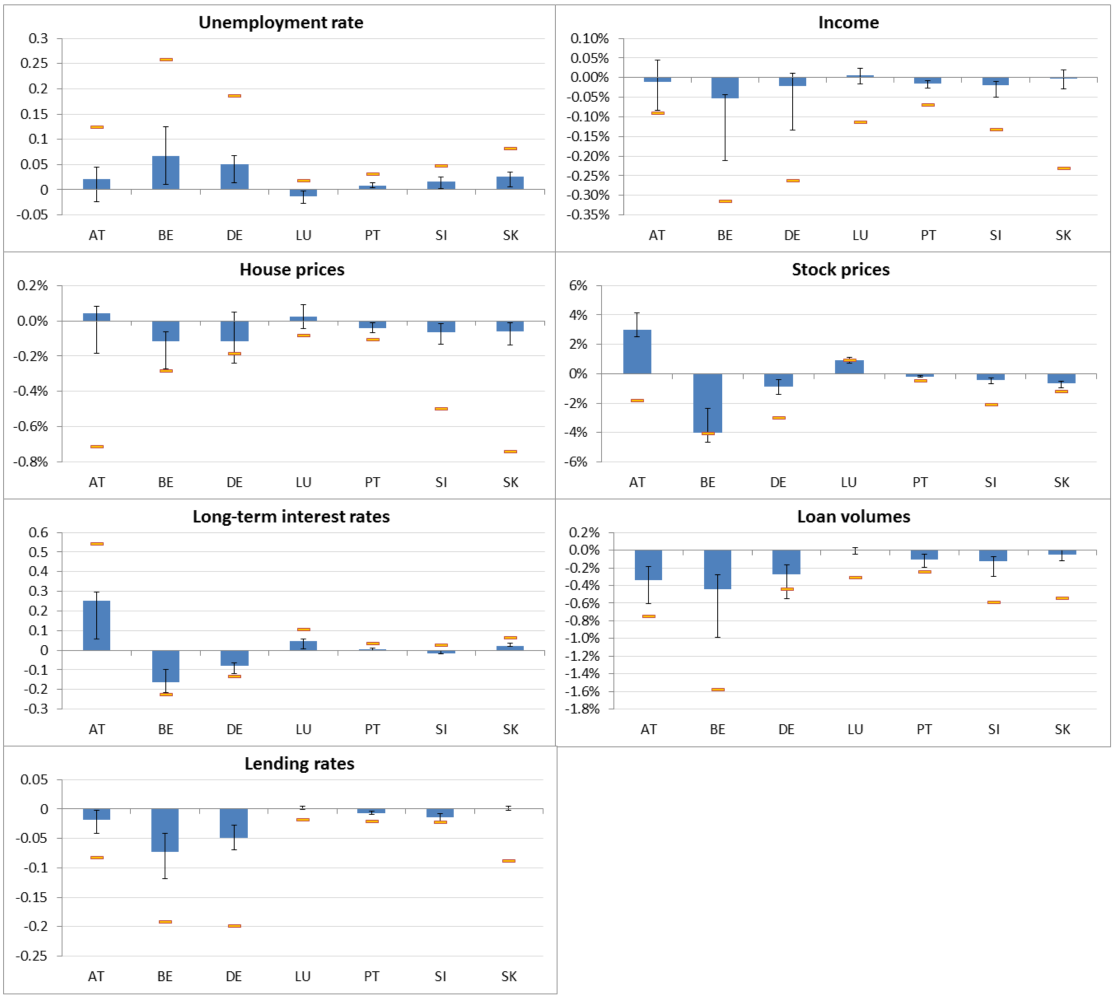
Note: The charts show the impact of LTV and DSTI caps, both along a grid on the horizontal axes, on probabilities of default (PD), loss given default (LGD), and loss rates for the aggregate household sector. The horizontal lines denote the aggregate baseline parameters resulting from the IDHBS model's implied PDs and LGDs for all individual households contained in the population. See Section 3.1 for details.

Figure 9: Macroeconomic responses to policy-induced loan demand shocks from LTV and DSTI caps (domestic effects only)



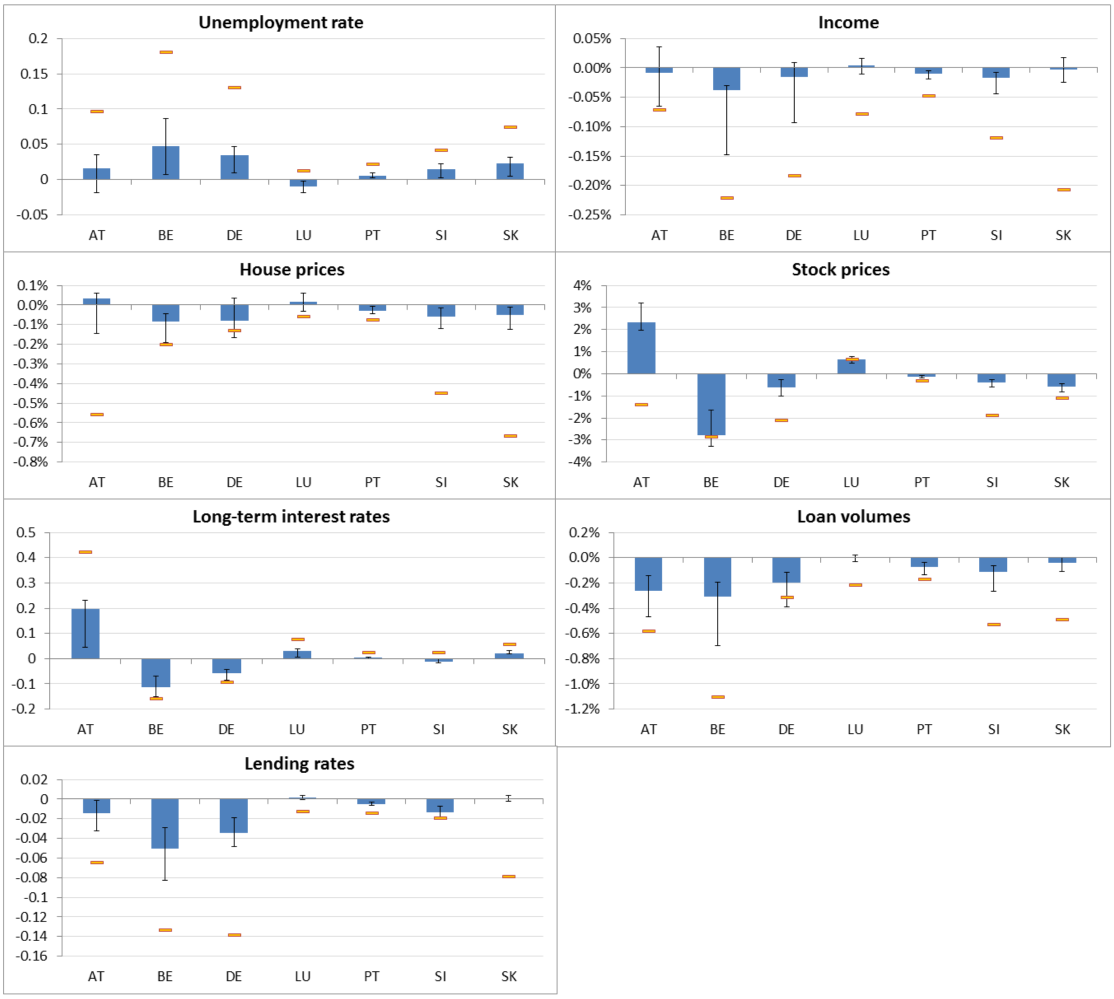
Note: The chart presents the macroeconomic responses to the LTV and LR-equivalent DSTI cap-induced loan demand shocks. The loan volume shock is coupled with a sign restriction on loan interest rates to fall along with volumes in the first quester of the simulation horizon. The responses are shown for Q1 and cumulative for the first 4 quarters (Q1:4) of the simulation horizon. The horizon extends further to three years in particular for the purpose of obtaining the house price profiles which are needed for the LGD calculations. See Section 2.2 for details.

Figure 10: Cross-border macroeconomic responses to policy-induced loan demand shocks from LTV caps



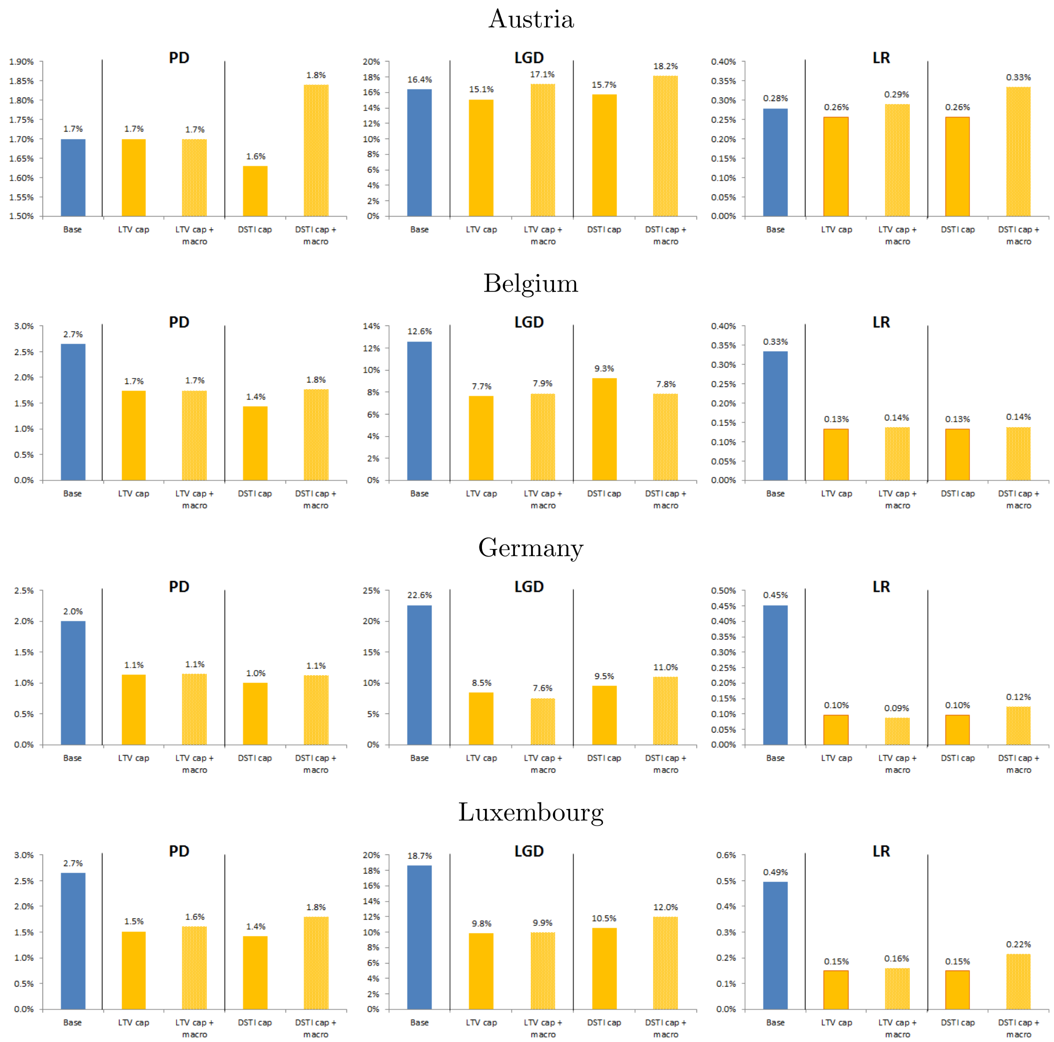
Note: The underlying policy-induced shocks to loan demand originate from the countries listed on the horizontal axes (one after another). The corresponding domestic responses of the variables are shown as orange horizontal bars (they correspond to the Q1:4 responses shown in Figure 9). The bars and surrounding error bars reflect the cross-country median and upper and lower quartiles across the 28 EU countries, excluding the country to which the shock was applied. All estimates reflect the cumulative responses over the first four quarters of the simulation horizon.

Figure 11: Cross-border macroeconomic responses to policy-induced loan demand shocks from DSTI caps



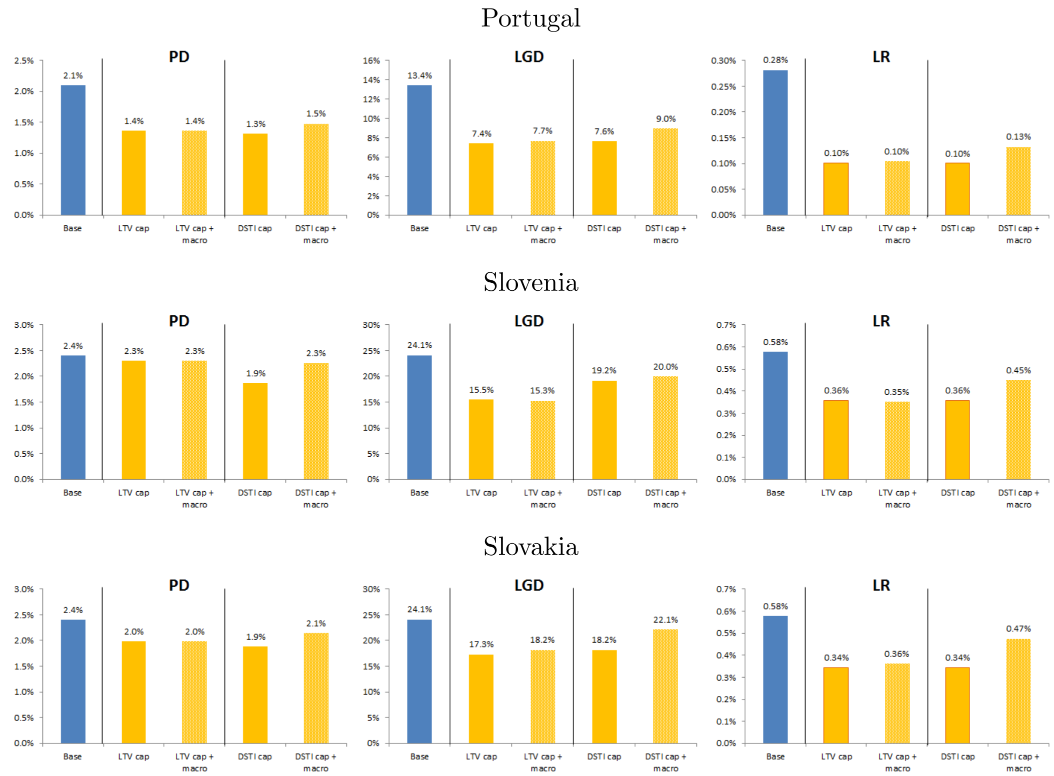
Note: The underlying policy-induced shocks to loan demand originate from the countries listed on the horizontal axes (one after another). The corresponding domestic responses of the variables are shown as orange horizontal bars (they correspond to the Q1:4 responses shown in Figure 9). The bars and surrounding error bars reflect the cross-country median and upper and lower quartiles across the 28 EU countries, excluding the country to which the shock was applied. All estimates reflect the cumulative responses over the first four quarters of the simulation horizon.

Figure 12: Impact of LTV cap at 85%, the loss rate-equivalent DSTI cap, and including macro feedback to household risk parameters



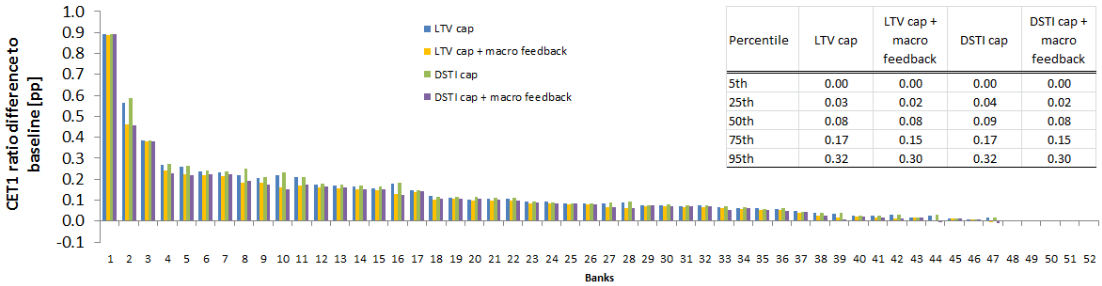
Note: The figures show the impact on households' PDs, LGDs, and loss rates after having imposed an LTV cap at 85% along with loss-rate equivalent DSTI caps. The individual households' responses are aggregated to household sector estimates by taking EAD-weighted averages for each country. See Section 3.2 for details.

Figure 13: Impact of LTV cap at 85%, the loss rate-equivalent DSTI cap, and including macro feedback to household risk parameters (continued)



Note: The figures show the impact on households' PDs, LGDs, and loss rates after having imposed an LTV cap at 85% along with loss-rate equivalent DSTI caps. The individual households' responses are aggregated to household sector estimates by taking EAD-weighted averages for each countrySee Section 3.2 for details.

Figure 14: Impact of LTV and DSTI caps on Common Equity Tier 1 position of 49 SSM banks



Percentile	LTV cap	LTV cap + macro feedback	DSTI cap	DSTI cap + macro feedback
5th	0.00	0.00	0.00	0.00
25th	0.03	0.02	0.04	0.02
50th	0.08	0.08	0.09	0.08
75th	0.17	0.15	0.17	0.15
95th	0.32	0.30	0.32	0.30

Note: The 49 SSM banks are from six of seven countries that are subject to the analysis (excluding Slovakia). The banks are sorted by the average impact over the four schemes (as indicated in the legend). See Section 3.3 for details.

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