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What Drives Mortgage Default Risk in Europe and the U.S.?

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ABSTRACT: We present an analysis of the sensitivity of household mortgage probabilities of default (PDs) and loss given default (LGDs) on unemployment rates, house price growth, interest rates, and other drivers. A structural micro-macro simulation model is used to that end. It is anchored in the balance sheets and income-expense flow data from about 95,000 households and 230,000 household members from 21 EU countries and the U.S. We present country-specific nonlinear regressions based on the structural model simulation-implied relation between PDs and LGDs and their drivers. These can be used for macro scenario-conditional forecasting, without requiring the conduct of the micro simulation. We also present a policy counterfactual analysis of the responsiveness of mortgage PDs, LGDs, and bank capitalization conditional on adverse scenarios related to the COVID-19 pandemic across all countries. The economics of debt moratoria and guarantees are discussed against the background of the model-based analysis.

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Contents

I. INTRODUCTION

This paper aims to examine the relationship between household mortgage probabilities of default (PDs) and loss given default (LGD) and their macroeconomic drivers, in a structural micro-macro simulation model, which is instrumental for conducting policy counterfactual analyses. The model is set up for 21 EU countries and the U.S. It can be used to obtain scenario-conditional forecasts of PDs and LGDs to assess household sector resilience and quantify the impact on banks. The scenario analysis can be intertwined with policy counterfactual assumptions. These include fiscal policy (e.g., regarding the design of unemployment benefits), macroprudential policy, and policies specific to the COVID-19 pandemic, such as debt moratoria and guarantees.

To that end, an enhanced version of the Integrated Dynamic Household Balance Sheet (IDHBS) model was developed. The IDHBS model (Gross and Población 2017, henceforth GP 2017) is a micro-macro simulation model that is used so far to assess the impact of borrower-based macroprudential policies on households and banks while accounting for macro-financial feedback (ECB 2016/17, Jurča et al. 2020, Neugebauer et al. 2021).[1] Since time series data for household risk metrics are hardly available publicly, such structural microsimulation approach is instrumental, including for bank stress testing, here for what concerns the banks' retail loan books. Even if time series data were available, time series models cannot be used to conduct as rich policy counterfactual analyses as with structural, microdata-based models. The model extensions beyond GP (2017) pertain to a nonlinear debt repayment mechanism and a distinction between variable and fixed rate loans, the inclusion of debt-holding pensioners, an extended interest income module, and a further refined LGD module.[2] We devise ex-post nonlinear regressions for PDs/LGDs from the microsimulation, which allow translating macro-financial scenarios into the risk metrics without requiring the conduct of the microsimulation but replicating its outcomes.

We show that in many countries, payment moratoria, as deployed during the COVID-19 pandemic, shielded households and banks' retail loan portfolios from significant stress that they would have experienced otherwise. Baseline and alternative, counterfactual scenario assumptions were taken from the IMF's *World Economic Outlook* (WEO) and combined with country-specific information about the design of the moratoria. The results suggest that moratoria had a notable role in containing households' credit risk, as well as in shielding banks from substantial retail portfolio-related credit losses. This result is much expected obviously. The model's avail lies in quantifying the effects on households and banks.

The model incorporates detailed country characteristics regarding labor and credit markets. These features include the details of unemployment benefit plans, for example, regarding replacement rates and the duration of benefits, the share of variable/fixed rate loans, and the extent to which house price developments influence PDs through strategic default incentives. Unemployment benefits and fixed interest rate shares differ notably across countries and have a significant impact on credit risk dynamics. The extent to which mortgages are limited recourse matters especially in the U.S., where strategic default incentives prevail to an extent, while EU countries mostly face full recourse systems. Our back-testing results of the model corroborate the model's ability to well capture the relevant channels through which macroeconomic conditions influence household PDs and LGDs.

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[1] The microdata are sourced from the Household Finance and Consumption Survey (HFCS) for the EU countries in the sample (link) and the Panel Survey of Income Dynamics (PSID) for the U.S. (link).

[2] The present paper has a companion one (see Giannoulakis et al. 2022) in which the same set of model extensions is considered, while the model is there being used to examine distributional aspects of PD and LGD responses, conditional on household wealth and income characteristics.

II. LITERATURE

The macroeconomic importance of household debt has been documented and motivates the analysis presented in this paper. The role of household debt dynamics—including in the U.S. in the run-up to the global financial crisis of 2007–09—is discussed in Mian and Sufi (2009, 2014) and Jòrda et al. (2013, 2016). The turning point analysis of Claessens et al. (2010) confirms that recessions are typically preceded by credit and housing booms. Similarly, based on cross-country panel data, Schularick and Taylor (2012) conclude that booms in credit and housing are strong predictors of subsequent recessions.

Microdata for households have been used to assess household debt dynamics and to conduct scenario analyses for households since the early 2000s (Table 1). The earliest contributions are found for Nordic European countries: Finland, Norway, and Sweden (Johansson and Persson 2006, Vatne 2006, Herrala and Kauko 2007). Analyses for European countries followed (Austria, Czech Republic, Hungary, Poland, and others), and for non-EU countries such as Korea (Karasulu 2008), Chile (Fuenzalida and Ruiz-Tagle 2011), Canada (Djoudad 2012), and Australia (Kearns et al. 2020). A survey can be found in Leika and Marchettini (2017).

This literature is largely descriptive, focusing on vulnerability metrics of different kinds. Such metrics include financial margins (income minus expenses), debt-service-to-income (DSTI) ratios, debt-to-asset ratios, and others. Scenario analyses are usually conducted to assess how such metrics behave in response to changing interest rates, unemployment rates, income, and house prices. None of them considers explicit multi-period scenario simulations, and virtually none of them provides estimates of PDs and LGDs. Various microdata analyses have also been undertaken in IMF FSAPs (Table 1).[3] Like the academic literature, they generally do not derive PDs and LGDs and thereby do not allow linking the household model outcome to bank stress tests. The model presented here can help accomplish this link, as also demonstrated in GP (2017) and Jurča et al. (2020).

Multi-period simulation frameworks for modeling household credit risk parameters have been developed in recent years. Such frameworks include Peterson and Roberts (2016) for Canada and GP (2017), developed at the European Central Bank (ECB) for European countries. These models consider an explicit simulation of the households' P&L flows and the implied balance sheet stocks and allow obtaining PDs and LGDs of a kind that is suitable to link to the corresponding bank credit risk metrics (considering, for example, a 90-day past due criterion for the computation of PDs).

Stochastic simulation methods are often employed when analyzing the impact of changing employment conditions on household risk metrics. The way such simulations are implemented—usually involving logistic employment models—differs across applications. Several papers develop procedures that assume that individuals have an equal probability of becoming unemployed by shifting the logistic regression's intercept in line with a macroeconomic scenario (Johansson and Persson 2006, Holló and Papp 2007, Albacete and Lindner 2010). Others allow controlling the transition flows by shifting the intercept for employed and unemployed households separately (Gapluščák et al. 2016), or in addition, matching the duration of unemployment via the addition of persistence terms in the logistic model's residual coupled with an intercept shift (GP 2017).

[3] Some model approaches that are not literally microsimulations but whose parameters are informed partly by microdata include Gornicka and Valderrama (2020) and IMF (2019, 2020).

Table 1. Literature—Micro Data Analyses and Models

#	Reference	Country	Financial margin, flow focus	Financial margin, flows and stocks	Forward-looking / scenario-conditional analysis													Link to bank balance sheets	Borrower-based MPRU policy	#
					Interest rates	Employ-ment	Income	House prices	Multi-variate scenarios	One-period/ instanta-neous	Multi-period horizon	Stochastic treatment of empl. status	Endogenous mortgage origination	PDs	LGDs			
1	**Johansson & Persson (2006)**	Sweden	✓		✓	✓	✓	✓		✓		✓						**1**
2	**Vatne (2006)**	Norway	✓		✓					✓								**2**
3	**Herrala & Kauko (2007)**	Finland	✓		✓	✓		✓		✓		✓						**3**
4	**Hollo & Papp (2007)**	Hungary	✓		✓	✓			✓	✓		✓		✓		✓		**4**
5	**Zajaczkowski & Zochowski (2007)**	Poland	✓		✓					✓								**5**
6	**Karasulu (2008)**	Korea		✓	✓			✓	✓	✓								**6**
7	**Albacete & Fessler (2010)**	Austria	✓		✓	✓		✓		✓		✓						**7**
8	**Fuenzalida & Ruiz-Tagle (2011)**	Chile	✓			✓				✓		✓						**8**
9	**IMF (2011)**	United Kingdom	✓		✓		✓	✓	✓	✓								**9**
10	**Costa & Farinha (2012)**	Portugal								✓								**10**
11	**Djoudad (2012)**	Canada	✓	✓	✓	✓	✓		✓			✓	✓					**11**
12	**IMF (2012)**	Spain	✓		✓	✓	✓	✓		✓		✓						**12**
13	**Albacete & Lindner (2013)**	Austria	✓							✓								**13**
14	**IMF (2013)**	Italy			✓		✓	✓	✓	✓								**14**
15	**Arins et al. (2014)**	Latvia		✓	✓	✓	✓		✓	✓		✓						**15**
16	**Lindquist et al. (2014)**	Norway	✓		✓			✓	✓	✓								**16**
17	**Michelangeli & Pietrunti (2014)**	Italy	✓		✓		✓			✓			✓					**17**
18	**Cussen et al. (2015)**	Ireland									✓						✓	**18**
19	**IMF (2015)**	Norway			✓		✓	✓	✓	✓								**19**
20	**Galuščák et al. (2016)**	Czech Republic	✓		✓	✓	✓		✓	✓		✓						**20**
21	**Peterson & Roberts (2016)**	Canada		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓				**21**
22	**Gross & Poblacion (2017)**	Euro area countries		✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	**22**
23	**IMF (2017a)**	Finland		✓			✓			✓								**23**
24	**IMF (2017b)**	Luxembourg	✓			✓	✓	✓	✓	✓								**24**
25	**Nier et al. (2019)**	Romania												✓			✓	**25**
26	**Jurča et al. (2020)**	Slovakia		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	**26**
27	**Neugebauer et al. (2021)**	Portugal		✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	**27**

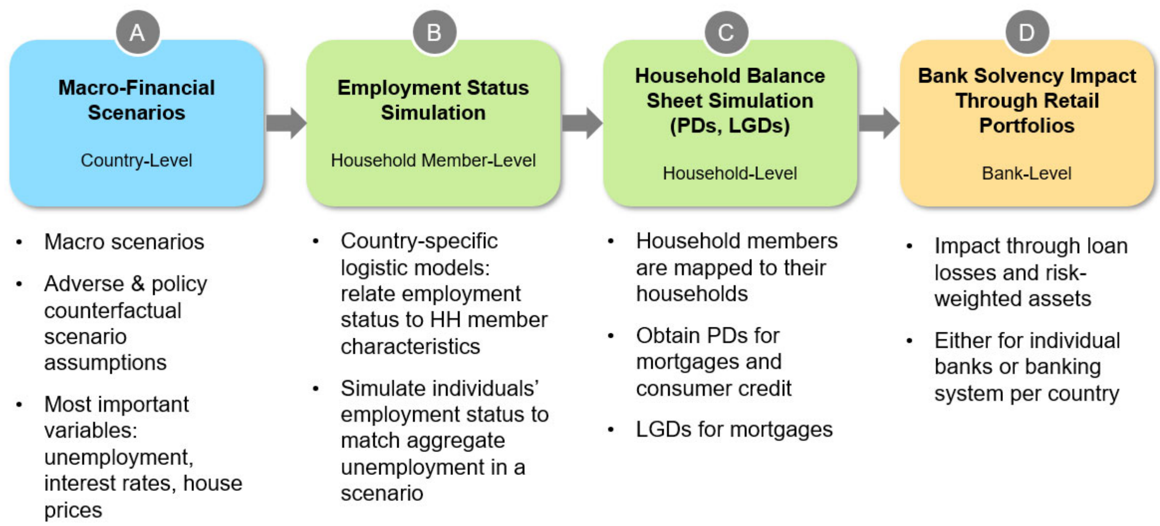
Note: The table summarizes a set of micro data-based analyses, either based on household micro data alone or in combined micro-macro model frameworks. MPRU abbreviate "macroprudential." See text for details.

III. The Micro-Macro Simulation Model

A. Model Structure

Our analysis builds on an enhanced version of the IDHBS model (GP 2017). Figure 1 shows a schematic of the model as employed here. Figure 2 presents a summary of the drivers that the model captures in a structural manner. Annex 1 contains a chart collection covering various variables and their distributions in the population and across countries based on the empirical microdata. Annex 2 reports how the microdata variables are mapped into the model.

Figure 1. Model Structure



Note: The schematic depicts the modified IDHBS model structure as used for scenario-conditional forecasting purposes in this paper.

Figure 2. Structural Drivers of Household Default and Loss Given Default Captured in the Model

	Primary Drivers	Secondary Drivers
Probability of Default (PD)	(1) **Unemployment** [+] (2) **Interest rates**, via - influencing deposit interest income [-] - interest expense for variable-rate debt [+] - bond valuation [secondary, +] (3) **House price growth**, in limited-recourse systems via changing strategic default incentive [-]	(4) **Income growth**, for - employed and self-employed HMs' income [-] - unemployed via anchoring replacement wage in previous employment income [-] (5) **Stock price returns**, for shareholders [-]
Loss Given Default (LGD)	(1) **House price growth** [-] (2) **Cure rate** [-] (3) **Interest rates** [+], for discounting under economic LGD model mode	(4) **Administrative costs** [+]

Note: The signs in brackets indicate the relationship (direct and ceteris paribus) between PDs/LGDs (specifically for mortgage debt) and their drivers, as captured in the structural model. The difference between primary and secondary drivers relates to their importance in terms of economic impact on PDs and LGDs.

Macro-financial scenarios as well as—optionally—counterfactual policy assumptions to be reflected at the micro level, are the input to the model (Figure 1, Module A). Five macro-financial variables are required to feed the model: unemployment rates, short-term interest rates, house prices, income growth (conditional on being employed), and stock price growth. Each macro-financial variable determines the evolution of specific flows and stocks at the household level, as will be explained throughout this section.

The employment model is used to simulate individual household members' employment status (Figure 1, Module B). The country-level logistic models relate the household members' employment status to structural characteristics, such as individuals' age, level of education, gender, marital status, and nationality (Annex 3). These models are used to generate a large number of stochastic draws (*D* repetitions) for all individuals while shifting the intercept of the logistic regressions and setting a persistence parameter, which jointly allow matching a population-level unemployment rate path and persistence in unemployment (see GP 2017 for details). The simulated unemployment status (*D* repetitions/rounds, all for *H* periods into the future) of individuals is then used as an input to Module C.

Retirees are included in the household member population, for whom PDs and LGDs are estimated as for the rest of the debt-holding population. While retirees are generally unlikely to default on their debt because of their stable income (from public or private and occupational pensions), they could in principle still experience debt service problems if they hold variable interest rate loans and have relatively small savings. Hence, while they are excluded from the employment status models and stochastic employment simulations, they form part of the household sample whose PDs and LGDs are computed. The share of retirees among households that hold mortgages or other consumer debt can be sizable in some countries, such as in Croatia, Greece, and the Netherlands (Annex 1).

Household Balance Sheet Dynamics and Probabilities of Default

The balance sheet simulator (Figure 1, Module C) produces *household-level PD and LGD estimates*. The module computes the path of all households' flows and implied balance sheet stocks conditional on a macro-financial scenario (house prices, wage growth, stock prices, interest rates).[4] Balance sheets, debt service, default, and the LGD-related calculations are simulated at the household level to which the individuals are mapped. The household-level stock of gross financial assets, $\mathrm{FA_t}$, comprises deposits, bonds, stocks, and shares of mutual funds and of life insurance and pension fund plans. The quarterly evolution of financial assets is determined by the flow of income and expenses, alongside some valuation effects:

$$\Delta \mathrm{FA_{hh,t}} = \underbrace{\mathrm{II_{hh,t}}}_{\substack{\text{Interest}\\\text{income, e.g.}\\\text{on deposits}}} + \underbrace{\mathrm{OI_{hh,t}}}_{\substack{\text{Other certain}\\\text{income, e.g.}\\\text{child benefit}\\\text{and alimony}}} - \underbrace{\mathrm{E_{hh,t}}}_{\substack{\text{Consumption}\\\text{expenses}}} - \underbrace{\mathrm{A_{hh,t}^{Tot,Q}}}_{\substack{\text{Debt service flow for}\\\text{consumer and/or}\\\text{mortgage debt}}} - \underbrace{\mathrm{OE_{hh,t}}}_{\substack{\text{Other}\\\text{expense,}\\\text{e.g. rent}}} + \underbrace{\begin{cases} \mathrm{INC_{n,t}^{E}}(1-\tau_c), & \text{empl. HH members} \\ \mathrm{INC_{n,t}^{U}}, & \text{unempl. HH members} \end{cases}}_{\substack{\text{Stochastically simulated and macro-consistent}\\\text{employment status of HH members from}\\\text{employment simulator (Module B) determines}\\\text{whether employment income or unemployment}\\\text{benefit is received}}} + \underbrace{\Delta \mathrm{B_{hh,t}}}_{\substack{\text{Change in}\\\text{market value}\\\text{of bonds}}} + \underbrace{\Delta \mathrm{S_{hh,t}}}_{\substack{\text{Change in}\\\text{market value}\\\text{of stocks}}} \tag{1}$$

where *n* counts the number of members of a household. In the first quarter of the simulation, the change in financial assets, $\Delta\mathrm{FA_{hh,t+1}}$, is anchored in the households' observed financial assets at the outset, the survey date. The unemployment benefit, $\mathrm{INC_{n,t}^{U}}$, is obtained by applying a country-specific replacement rate to the household members' most recent gross employment

[4] The equations in the following omit an explicit indexing to denote the simulation rounds *d=1…D*, for the sake of brevity.

income $INC^{E}_{n,t}$, subject to an absolute ceiling that is informed by country-specific legislation and the maxima and upper percentiles in the micro dataset itself.

Three model options are considered for the consumption expenditure process. These include the following:

$$(2)\quad E_{hh,t+h} = \begin{cases} \frac{E_{hh,t_0}}{GI_{hh,t_0}} \times GI_{hh,t_0} & \underline{\text{Mode 1}}\text{: Relative expenditure-to-gross income ratio at HH level constant} \\ \left(\frac{E}{GI}\right)_c \times GI_{hh,t_0} & \underline{\text{Mode 2}}\text{: Population-level expenditure-to-gross income ratio constant} \\ E_{hh,t_0} & \underline{\text{Mode 3}}\text{: HH level absolute expenditure constant} \end{cases}$$

Mode 3 is used as a base case mode.

The debt expense flow ($A^{Tot,Q}_{t}$) in eq. (1) comprises interest expenses and principal repayment of mortgage debt and consumer debt.[5] The subsequent PDs at population level are computed specifically as *mortgage* exposure-weighted averages, that is, assigning zero weight to consumer debt-only households, as specific interest lies in mortgages in this paper. By nature of the LGD model, the LGDs are computed only for households with mortgage debt, of which mortgage debt-weighted country aggregates are computed just as for PDs. Details on the annuity and the dynamic calculation of its components follow shortly.

Households' bond and stock holdings are revalued based on the interest rate and stock price paths. The value of households' share holdings ($S_{hh,t}$) is linked to the country-aggregate log stock price return ($RET_{c,t}$) from a scenario. A modified duration approach is used to revalue their bond holdings ($B_{hh,t}$), assuming a $D = 2$-year average bond duration.[6]

$$(3)\qquad S_{hh,t} = \exp\left(\ln\left(S_{hh,t-1}\right) + RET_{c,t}\right) \text{ and } B_{hh,t} = B_{hh,t-1}\left(1 - \frac{D}{1+r^{SIM}_{c,t-1}} \times \Delta r^{SIM}_{c,t}\right)$$

Default is defined to occur when a household cannot service its combined annuity for at least one quarter. The default rule is:

$$(4)\qquad \text{Default in } t+h \coloneqq \begin{cases} 1 & \text{if } FA_{hh,t+h} < 0 \\ 0 & \text{otherwise} \end{cases}$$

Optionally, the default process takes house price developments into account. The overlay is used for countries where strategic default incentives matter due to a more limited recourse structure. A "negative equity" criterion is added to the default rule in this case:

$$(5)\qquad \text{Default in } t+h^* \coloneqq \begin{cases} 1 & \text{if } FA_{hh,t+h} < 0 \text{ or } V_{hh,t+h} < P_{hh,t+h} \\ 0 & \text{otherwise} \end{cases}$$

where $V_{hh,t+h}$ is the house value that is aligned with a scenario path: $V_{hh,t} = \exp\left(\ln\left(V_{hh,t-1}\right) + HPG_{c,t}\right)$. $P_{hh,t+h}$ is the principal debt balance that falls by the quarterly

[5] There is currently no consideration of consumer debt being defaulted first in order to increase the repayment capacity for mortgages. This is a refinement of the model that can be considered in the future. Currently, the PDs estimated for a household reflect the default probability for their *combined* mortgage and consumer debt.

[6] The choice of the average duration parameter has only a negligible impact on the results, because households' bond holdings are small in all countries. See Annex 2.

principal repayment flow: $P_{hh,t+h} = P_{hh,t+h-1} - A^{P}_{hh,t+h}$. The dynamics of the principal repayment $A^{P}_{hh,t+h}$ are described next.

Fixed and Variable Interest Rate Loan Contracts and Related Calculations

The model distinguishes between fixed and variable rate debt. This is meant to properly capture the dependence of PDs on interest rates. The information about the interest rate type of households' individual outstanding debt contracts is contained in the microdata and used in the model.[7]

A nonlinear repayment schedule is designed for all debt-holding households.[8] The initial residual duration *M* in months for each debt-holding household is first approximated as a function of the reported household loan-specific annual interest rate i_{hh,t_0}, the currently outstanding principal debt stock P_{hh,t_0}, and the current quarterly annuity flow, $A^{Tot,Q}_{hh}$; all as reported as of the survey date and for households' "synthetically combined" debt (mortgage plus consumer debt):

$$(6) \qquad M_{hh,t_0} = \frac{\log\left(\frac{4A^{Tot,Q}_{hh}}{4A^{Tot,Q}_{hh} - i_{hh,t_0} P_{hh,t_0}}\right)}{\log\left({}^{i_{hh,t_0}}/_{12}+1\right)}$$

M computed from this equation is rounded up to the nearest integer. An indicator of whether the debt is of a variable or fixed rate type is based on the outstanding mortgage.[9] For fixed rate loans, the monthly interest payment flow, $A^{I,fixed}_{hh,t+s}$, and their monthly principal repayment flows, $A^{P,fixed}_{hh,t+s}$, are:

$$(7) \qquad A^{I,fixed}_{hh,t+s} = i_{hh,t_0}/12 \times P_{hh,t+s-1} \;\text{ and }\; A^{P,fixed}_{hh,t+s} = A^{Tot,fixed}_{hh} - A^{I,fixed}_{hh,t+s}$$

For variable rate loans, the monthly interest payment flow, $A^{I,var}_{hh,t+s}$, is a function of a variable interest rate path, $i_{hh,t+s-1}$:

$$(8) \qquad A^{I,var}_{hh,t+s} = \frac{i_{hh,t+s-1} \times P_{hh,t+s-1}}{12}$$

where a variable rate loan's $i_{hh,t+s-1}$ evolves endogenously in parallel to the short-term interest rate from a scenario, r^{sim}_{t+s}, as follows:

$$(9) \qquad i_{hh,t+s} = \max\left(0, i_{hh,t+s-1} + \Delta r^{sim}_{t+s}\right)$$

The total monthly annuity for variable rate loans, $A^{Tot,var}_{hh,t+s}$, and the principal repayment flow, $A^{P,var}_{hh,t+s}$, are computed every month as:

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[7] For where households report that they do not know about the interest fixation type, the choice is assigned in line with the predominant interest rate type in a country. The criterion for the latter is whether the fixed-variable rate share exceeds/falls short of 50 percent in 2017. See Annex 2.

[8] The primary model extension relative to GP (2017) was the fixed-variable rate distinction, while the nonlinear repayment feature was then a natural and easy extension to consider in addition. The nonlinear repayment scheme should enhance the precision of the estimated PDs as this feature well aligns with contract design in reality.

[9] Mortgage debt balances are by a sizable margin larger than outstanding consumer debt, which justifies the approximation to assume the interest rate type reported of a mortgage for the households' total debt.

$$(10) \quad A^{\mathrm{Tot,var}}_{\mathrm{hh,t+s}} = P_{\mathrm{hh,t+s-1}} \frac{\frac{i_{\mathrm{hh,t+s}}}{12}\left(1+i_{\mathrm{hh,t+s}}/12\right)^{M^{\mathrm{res}}_{\mathrm{hh,t+s}}}}{\left(1+i_{\mathrm{hh,t+s-1}}/12\right)^{M^{\mathrm{res}}_{\mathrm{hh,t+s}}-1}} \quad \text{and} \quad A^{\mathrm{P,var}}_{\mathrm{hh,t+s}} = A^{\mathrm{Tot,var}}_{\mathrm{hh,t+s}} - A^{\mathrm{I,var}}_{\mathrm{hh,t+s}}$$

where $M^{\mathrm{res}}_{\mathrm{hh,t+s}}$ is the residual maturity in months, which evolves as $M^{\mathrm{res}}_{\mathrm{hh,t+s}} = M^{\mathrm{res}}_{\mathrm{hh,t+s-1}} - 1$. The interest and principal flow calculations are conducted at a monthly frequency, but then converted to quarterly to be compatible with the quarterly frequency of the model simulation. This entails taking sums of principal and interest payment flows in non-overlapping steps of three months going forward in time. The monthly time steps in the equations here are denoted by *s* to distinguish them from quarterly steps, denoted by *h*, elsewhere in this section.

LGD Model Component

The LGD module relates the house value to a house price path. First, each household's predicted housing collateral sales value, $V_{\mathrm{hh,t_0+H}}$, at the future time of resolution ($t_0 + H$ quarters), is projected in line with a scenario path for quarter-on-quarter log house price growth (HPG). A household-specific claim that a bank attempts to recover is denoted as $\mathrm{Claim_{hh}}$. *C* captures administrative and legal costs measured as a percentage of outstanding principal, and $i^{\mathrm{MORT,eff}}_{\mathrm{hh,t_0}}$ is the effective mortgage loan interest rate at household-level. With these terms, the nominal expected recovery value, $\mathrm{ERV_{hh}}$, can be defined as:

$$(11) \quad \mathrm{ERV_{hh}} = \min\Big(\underbrace{\exp\left(\ln\left(V_{\mathrm{hh,t_0}}\right) + \textstyle\sum_{h=1}^{H} \mathrm{HPG}_{t=h}\right)}_{V_{\mathrm{hh,t_0+H}}}, \underbrace{\left(1 + C + 0.25 \times i^{\mathrm{MORT,eff}}_{\mathrm{hh,t_0}}\right) P^{\mathrm{MORT}}_{\mathrm{hh,t_0}}}_{\mathrm{Claim_{hh}}}\Big)$$

The inclusion of a quarter of the annual effective mortgage rate in the claim term reflects that interest payments over 90 days (three months) were missed and are capitalized by assumption. The minimum operator around the two terms in eq. (11) reflects bankruptcy law, which generally stipulates that if the recovery value exceeds an outstanding claim, the difference must be credited back to the defaulted borrower. The LGD as defined here does not account explicitly for recourse to defaulted borrowers' future income. This is difficult to model.

The model allows switching between an accounting and an economic mode regarding the treatment of the discount rate in the LGD module. Under the accounting mode, a household's reported effective mortgage interest rate as of the survey date, $i^{\mathrm{MORT,eff}}_{\mathrm{hh,t_0}}$, is used for discounting the expected recovery value. Under the economic mode, an expected return measure for mortgages at the country level, $R_{\mathrm{c,t_0}}$,, is used for discounting, which is, moreover, time-varying by letting it move parallel to the short-term interest rate ($r_{\mathrm{c,t}}$) in a scenario; that is, $R_{\mathrm{c,t_0}+h} = R_{\mathrm{c,t_0}} + r_{\mathrm{c,t_0}+h} - r_{\mathrm{c,t_0}}$. The country-level expected return on mortgages at the outset, $R_{\mathrm{c,t_0}}$, is computed as:

$$(12) \quad R_{\mathrm{c,t_0}} = i^{\mathrm{MORT,eff}}_{\mathrm{c,t_0}} - \frac{\mathrm{PD_c} \times \mathrm{LGD_c}}{1 - \mathrm{PD_c}}$$

where the term that is subtracted here measures the expected loss component of the effective interest rate, i.e., a credit spread.[10] The discount factor for mortgage holding households, $\mathrm{DF_{hh}}$, is:

$$\text{(13)}\quad \mathrm{DF_{hh}} = \begin{cases} \left(1 + {i_{hh,t_0}^{MORT,eff}}/{12}\right)^{-3H} & \text{in accounting LGD mode} \\ \left(1 + {\overline{R_{c,t=1\ldots H}}}/{12}\right)^{-3H} & \text{in economic LGD mode} \end{cases}$$

where $\overline{R_{c,t=1\ldots H}}$ is the average of the expected return path along the horizon up to resolution time. The final LGD is computed as:

$$\text{(14)}\quad \mathrm{LGD_{hh}} = (1 - \mathrm{CP_c})\left(1 - \frac{\mathrm{DF_{hh}} \times \mathrm{ERV_{hh}}}{\mathrm{Claim_{hh}}}\right)$$

$\mathrm{CP_c}$ is a country-specific cure probability.

The choice between the accounting and economic LGD mode depends on the purpose of the simulations. The accounting mode is useful when the aim is to use the LGD simulation output to link to bank portfolios and compute accounting-based losses and the impact on banks' capital. Accounting rules stipulate the use of an effective interest rate for discounting (IAS 39 [International Accounting Standards], IFRS 9 [International Financial Reporting Standards], CECL [Current Expected Credit Losses]). This approach has some drawbacks, however: (1) for fixed rate loans, it is a contract rate from origination, which can be outdated and not reflect current and expected economic conditions well; (2) it contains a loan-specific risk premium, rendering the discount rate too high if the objective is to use discounting for capturing the forgone *expected return* of an asset class under scrutiny; and (3) using a contract rate means neglecting a future *expected* interest rate path. The economic LGD mode, as designed here, resolves these three issues. Useful entry points to a (small) literature on the choice of discount rates for LGD model purposes include GCD (2017) and EBA (2017). While economically meaningful and not very data demanding, the PD and LGD-based calculation of a credit spread for obtaining an expected return for discounting, as done here in eq. (12), has not been considered elsewhere yet to our knowledge.

In summary, five additional features enhance the original GP (2017) framework for the analysis presented here. They comprise: (1) the nonlinear repayment schedules for fixed and variable rate loans, as described earlier; (2) the distinction of the accounting and economic mode for the LGD module; (3) the inclusion of debt-holding pensioners; (4) interest income on deposits is considered, including the pass-through from money market rates to deposits rates; and (5) the inclusion of country-specific unemployment benefit ceilings.

B. Data and Model Parameters

The model is anchored in the survey microdata of the EU HFCS and U.S. PSID. Table 2 shows the country coverage and some summary statistics. Both survey waves correspond to the year 2017. The HFCS and PSID survey samples are assumed to be representative of the

[10] It was derived from a simple cost-to-expected-net interest income equating pricing equation: PD×LGD+(1-PD)(μ+f)=(1-PD)i↔i=(PD×LGD)/(1-PD)+μ+f, where f is a measure of the cost of the liability (deposit) that is created through granting a loan and μ is a profit margin, which, if positive, implies the potential to generate positive net interest income and remunerating bank shareholders.

population totals, which the respective publicly available survey documentations suggest (see ECB 2020, Section 4, and PSID 2019, Section 2).

Various model parameters were calibrated based on country-level data obtained from the OECD and other sources. These include income tax rates, unemployment benefit replacement rates relative to previous gross-of-tax income, and an absolute ceiling on unemployment benefits (Table 3).

Table 2. Household Micro Data—Summary Statistics

		HHs	HMs	HMs / HHs	HHs with mortgage	.../ # HHs	HHs with consumer debt	.../ # HHs	HHs with debt	.../ # HHs	Initial LTV (mortgages)	Current LTV (mortgages)	Current DSTI (total debt)	Current DTI (total debt)	
Euro Area (EA) / EU	AT	3,072	6,414	2.1	418	14%	646	21%	962	31%	63%	24%	8%	24%	AT
	BE	2,329	5,370	2.3	722	31%	618	27%	1,071	46%	81%	29%	13%	59%	BE
	CY	1,303	4,188	3.2	574	44%	490	38%	805	62%	79%	44%	26%	194%	CY
	DE	4,942	11,251	2.3	1,356	27%	1,388	28%	2,253	46%	59%	32%	11%	60%	DE
	EE	2,679	6,724	2.5	649	24%	1,179	44%	1,399	52%	94%	42%	8%	22%	EE
	FI	10,210	24,818	2.4	4,421	43%	5,013	49%	6,572	64%	-	43%	12%	87%	FI
	FR	13,685	32,799	2.4	4,560	33%	4,342	32%	7,040	51%	81%	43%	18%	84%	FR
	GR	3,007	7,463	2.5	293	10%	319	11%	570	19%	100%	50%	13%	66%	GR
	IE	4,793	12,778	2.7	1,439	30%	1,738	36%	2,401	50%	88%	43%	13%	68%	IE
	IT	7,420	16,462	2.2	478	6%	1,019	14%	1,340	18%	80%	35%	12%	32%	IT
	LT	1,664	3,729	2.2	203	12%	339	20%	483	29%	89%	44%	10%	34%	LT
	LU	1,616	4,384	2.7	629	39%	589	36%	951	59%	86%	38%	15%	112%	LU
	LV	1,249	2,824	2.3	200	16%	376	30%	486	39%	109%	48%	10%	24%	LV
	MT	1,004	2,632	2.6	155	15%	191	19%	282	28%	90%	36%	12%	78%	MT
	NL	2,556	5,250	2.1	1,345	53%	394	15%	1,531	60%	98%	63%	12%	236%	NL
	PT	5,924	15,079	2.5	2,159	36%	1,277	22%	2,749	46%	90%	41%	14%	134%	PT
	SI	2,014	5,405	2.7	190	9%	580	29%	690	34%	72%	33%	11%	22%	SI
	SK	2,179	5,307	2.4	322	15%	393	18%	620	28%	100%	40%	12%	54%	SK
Non-EA EU	HR	1,357	3,699	2.7	121	9%	488	36%	550	41%	81%	25%	18%	28%	HR
	HU	5,968	13,937	2.3	994	17%	1,054	18%	1,733	29%	71%	27%	11%	39%	HU
	PL	5,858	15,017	2.6	743	13%	1,738	30%	2,169	37%	76%	30%	11%	15%	PL
Non-EU	US	9,607	24,998	2.6	3,036	32%	4,734	49%	5,924	62%	-	64%	14%	87%	US
Total		**94,436**	**230,528**	**2.4**	**25,007**	**26%**	**28,905**	**31%**	**42,581**	**45%**	**83%**	**40%**	**12%**	**60%**	**Total**

Sources: HFCS for European countries, PSID for the US, and author calculations. The loan-to-value (LTV), debt-service-to-income (DSTI), and debt-to-income (DTI) ratios are medians based on the underlying debt-holding household population.

Table 3. Income Tax Rates, Replacement Rates, and Unemployment Benefit Ceilings

		AT	BE	CY	DE	EE	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK	US
Unemployment benefit, replacement rate (relative to previous gross-of-tax income)	Year 1	38%	44%	36%	41%	40%	38%	54%	21%	34%	14%	36%	43%	35%	66%	41%	30%	50%	33%	56%	40%	33%	17%
	Year 2	36%	35%	28%	24%	22%	35%	54%	11%	18%	8%	36%	28%	10%	35%	18%	33%	50%	17%	53%	24%	13%	5%
	Year 3	36%	33%	28%	24%	22%	31%	29%	11%	17%	8%	36%	0%	10%	35%	18%	33%	41%	17%	24%	24%	13%	5%
	Av. Year1-3	37%	37%	31%	30%	28%	35%	45%	14%	23%	10%	36%	24%	18%	45%	26%	32%	47%	22%	45%	30%	19%	9%
Unemployment benefit, ceiling (*)		1,250	1,800	1,000	1,500	400	1,650	3,500	350	300	150	1,500	1,200	800	2,250	500	400	2,800	500	800	350	350	2,100
Income tax rate		29%	33%	25%	30%	14%	30%	22%	26%	25%	28%	20%	28%	36%	23%	24%	25%	28%	22%	22%	25%	19%	17%

Sources: OECD, EC, HFCS. (*) In euros for all countries except the U.S.; in U.S. dollars for the U.S.. All parameters for the year 2017.

For both mortgage PDs and LGDs at the country level, external "anchor values" were employed. An adjustment was considered to account for differences between raw model outputs—which might not be fully representative of the population-level risk parameters—and the external "anchor" values. Default rate starting points for 2017 (the survey date) were sourced from the EBA Risk Dashboard.[11] LGD starting points were informed by banks' reported coverage ratios for their mortgage portfolios (locational perspective) in the EBA/ECB/SSM (European Banking Authority/European Central Bank/Single Supervisory Mechanism) stress test 2018, and rounded up to the nearest 5 p.p. increment.[12] The anchoring was done by first computing "raw" PDs and LGDs under a baseline simulation mode, with the macro paths aligned with realized outcomes for the year 2017, and then shifting them in absolute terms to match the external anchor values. Table 4 reports the PD and LGD anchor

[11] https://eba.europa.eu/risk-analysis-and-data/risk-dashboard.

[12] https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2018.

values, which were sourced from the EBA risk dashboards. It also shows the country level mortgage interest rates for 2017, and the implied expected return measure starting points, computed using eq. (12). The latter are visualized in Figure 3.[13]

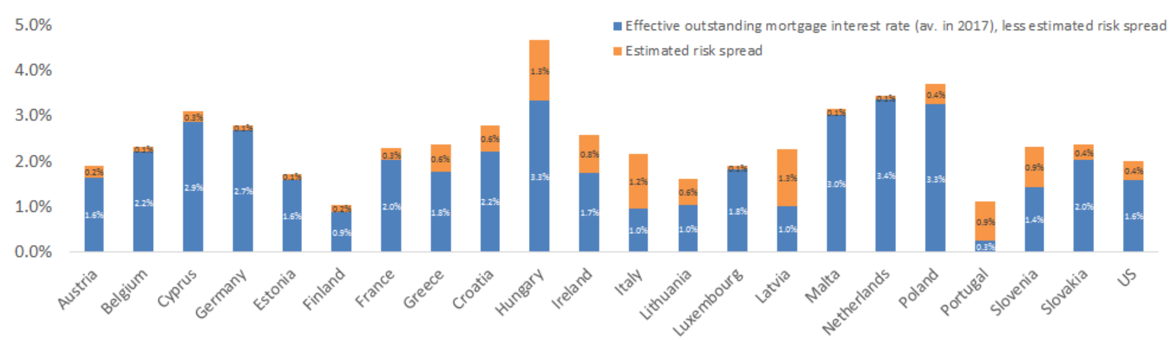
Table 4. Mortgage PD and LGD "Anchor Points," Expected Return Estimates for Mortgage Loans, and Cure Rate Assumptions

	AT	BE	CY	DE	EE	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK	US
PD anchor point (mortgages)	1.2%	1.1%	1.3%	0.7%	0.5%	1.5%	1.0%	3.0%	1.4%	3.3%	4.0%	3.9%	1.7%	0.7%	2.7%	0.6%	0.7%	1.1%	3.3%	4.2%	0.9%	0.6%
LGD anchor point (mortgages)	20%	10%	20%	15%	25%	10%	25%	20%	40%	40%	20%	30%	35%	10%	45%	20%	10%	40%	25%	20%	40%	10%
Mortgage interest rate, 2017	1.9%	2.3%	3.1%	2.8%	1.7%	1.0%	2.3%	2.4%	2.8%	4.7%	2.6%	2.2%	1.6%	1.9%	2.3%	3.1%	3.4%	3.7%	1.1%	2.3%	2.4%	3.3%
Estimated expected return on mortgages, 2	1.6%	2.2%	2.9%	2.7%	1.6%	0.9%	2.0%	1.8%	2.2%	3.3%	1.7%	1.0%	1.0%	1.8%	1.0%	3.0%	3.4%	3.3%	0.3%	1.4%	2.0%	3.2%
Cure rate	5%	5%	10%	10%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	25%	5%	5%	5%	5%	5%

Sources: EBA, ECB, and author calculations.

The LGD module's parameters complete the model calibration. The cost percentage (C) was set to 5 percent for all countries and kept fixed during the simulations.[14] The collateral sales period, that is, H in eq. (11), was set to eight quarters. The initial cure probability (CP) was set for each country on a grid from 5 to 40 percent (in 5 p.p. increments), choosing it from that grid so that the baseline simulation-based ("raw") LGD for a country came closest to the external benchmark LGD. The cure probability assumptions are included in Table 4.

Figure 3. Effective Mortgage Interest Rates and Estimated Risk Spread Component



Source: ECB and author calculations.

IV. Model Simulations

The grid-based simulation was run to assess the dependence of PDs and LGDs on their drivers. Grids with 20 equally spaced points for each variable's range were set up for:

- the unemployment rate, from 3 to 15 percent[15]
- interest rates, from 0 to 10 percent
- stock price growth, from -50 to 25 annual log percent
- compensation per employee growth, from -10 to 20 annual log percent

[13] For the LGD Year-0 anchor point data, the model users should in principle be mindful of distinguishing accounting-type ones, involving effective loan rates for discounting, as opposed to economic ones, having involved other discounting methods (expected returns, weighted average cost of funding, or others). Publicly available data are limited, rendering this consideration largely conceptual. Internal bank data are richer and can allow for doing a precise distinction and use of respective starting points depending on the model's LGD mode.

[14] This judgmental assumption is not very influential for the results. Changing the cost percentage for example to 2.5 or 7.5 percent, and re-doing the anchoring, implies no notable changes for the scenario responses.

[15] For Greece, the unemployment rate grid was set to range from 10 to 25 percent, because its unemployment rate over the years 2017–19. The ranges are otherwise defined as a common grid for all countries, disregarding country-specific historical distributions, to facilitate a cross-country comparison of the resulting elasticities (next section). They can still be interpreted with a focus on the historically relevant ranges.

- residential house price growth, from -50 to 25 annual log percent
- the cure rate parameter, from 5 to 40 percent

For PDs, the grids for unemployment rates, interest rates, stock price growth, and compensation growth were employed. For no-recourse countries, the house price growth grid was also considered while activating the strategic default incentive overlay (eq. 5). For the LGDs, the house price growth, cure rate grid, and interest rate grid under the economic LGD mode were considered. Under the accounting LGD mode, the interest rate dependence disappears by design.

Second-order polynomials were fitted to the simulation outcomes. The polynomials have the simulated PD and LGD responses on the left hand-side and the respective grids on the equations' right side.

A. Determinants of Mortgage PDs

The expected primary drivers of PDs—unemployment rates and interest rates—are found to influence PDs to a notable extent. The positive dependence regarding both drivers is visible in Figure 4, which reflect ceteris paribus shifts. That is, if an unemployment rate level is assumed to stand at a certain elevated level, the PDs would likely be yet to an extent larger than indicated in these plots, because other drivers—for example, income per employee growth—may exert further pressure on the PDs. The scenario analysis in Section VI addresses this aspect by involving consistent multivariate macro-financial scenarios.

Figure 5 shows the *average* PD sensitivities to all drivers. They were obtained by regressing the logit-transformed PDs from the microsimulation on the respective drivers' grids.[16] They ignore any nonlinearities (as visible in Figure 4) on purpose to obtain a summary measure of the sensitivity. Countries such as Poland, Slovakia, and the U.S. rank high for PD sensitivity to unemployment rate changes. European countries such as France, Germany, Italy, and the Netherlands are all seen to depend least on unemployment, for the country sample under scrutiny. Large European countries' as well as the U.S.'s mortgage PDs are not very sensitive to short-term interest rate changes. The stock price growth dependence is visible in the few countries where households hold a somewhat larger portion of their financial assets in stocks (Annex 1).

The cross-country heterogeneity of the sensitivities can be well explained by structural labor market and loan contract design characteristics across countries. The average PD dependence with respect to unemployment rates correlates well with population-level wage replacement rates (Figure 6, left). The PD dependence with respect to interest rate dynamics correlates well with variable rate contract shares (Figure 6, right). Such ex-post relationships are not supposed to be "perfect" (that is, R-squares as in Figure 6 do not need to be very high or close to 100 percent), because such structural features are not the only determinants of the PD sensitivities. Cash stocks, for example, matter as well. Yet, it is nonetheless useful to see such relationships surfacing, as they are expected to be the rather dominant ones.

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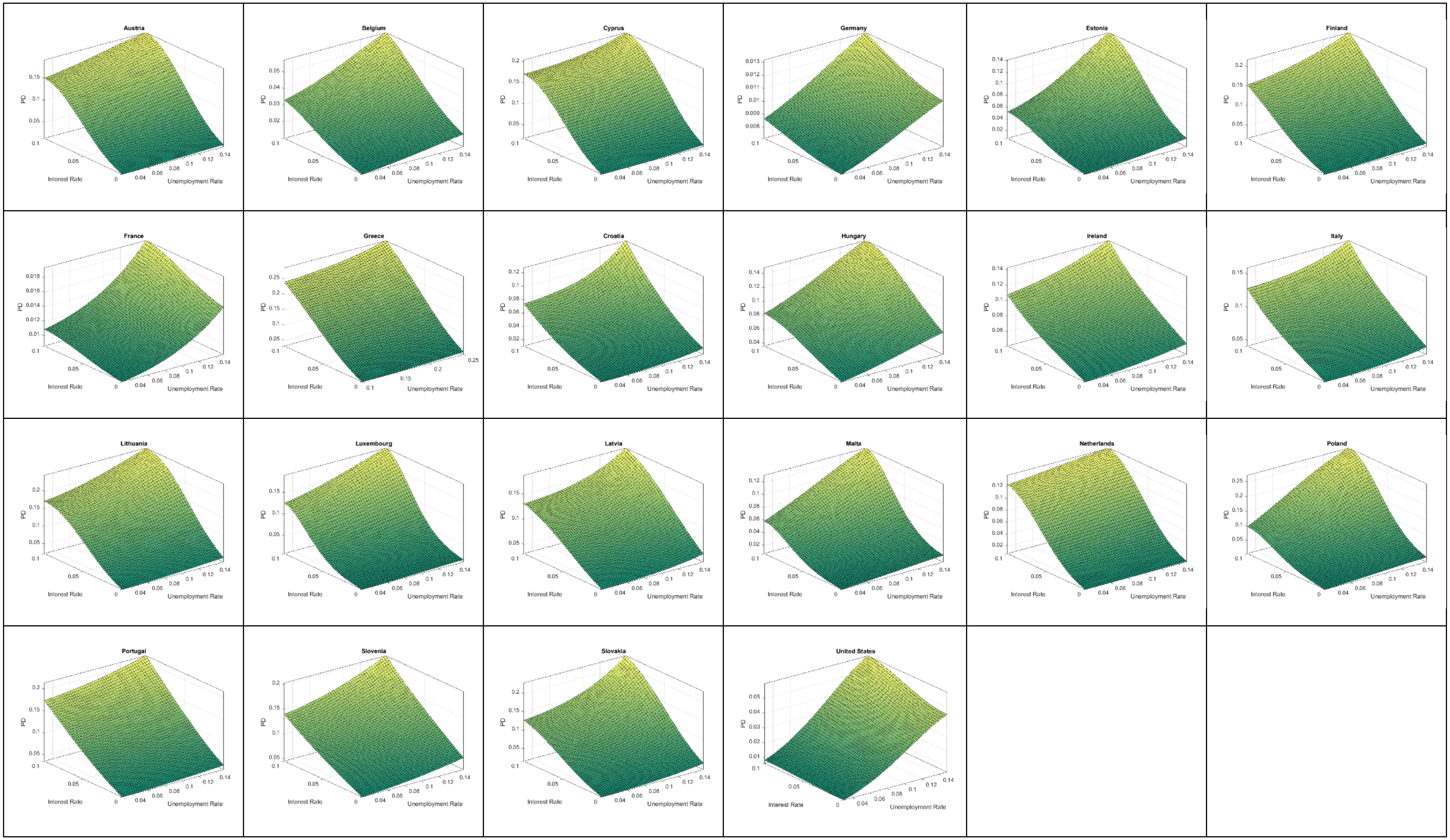
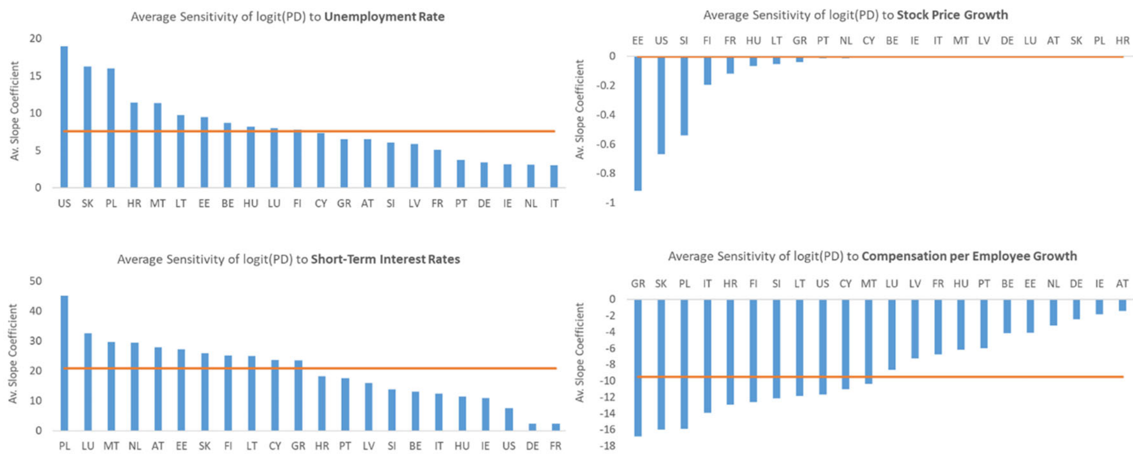
[16] They were obtained initially for the different drivers separately, from their related grid-based simulations holding all other factors constant. The sensitivities were then combined to a multivariate equation, implying the intercept so that the external anchor value was matched. Combining the multivariate sensitivities in this way can be done because the structural simulations are ceteris paribus by design, reflecting a multivariate regression model philosophy.

Figure 4. Dependence of Mortgage PDs on Unemployment Rates and Interest Rates (Ceteris Paribus Shifts)



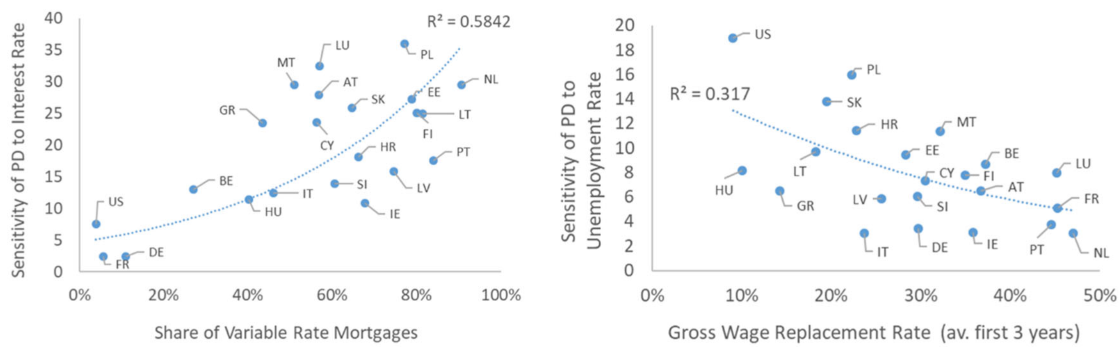
Note: The figures visualize the dependence of household mortgage PDs on interest rates and unemployment rates. All other relevant drivers are held constant for the purpose of the derivation of this trivariate dependence from the structural simulation model. See text for details.

Figure 5. Average Sensitivities of PDs to Their Drivers



Note: The average sensitivities are obtained by regressing the logit-transformed PD responses for all countries (resulting from the microsimulation) on the respective grids of the drivers. Such grids were defined using a common range across countries. Orange: median across countries.

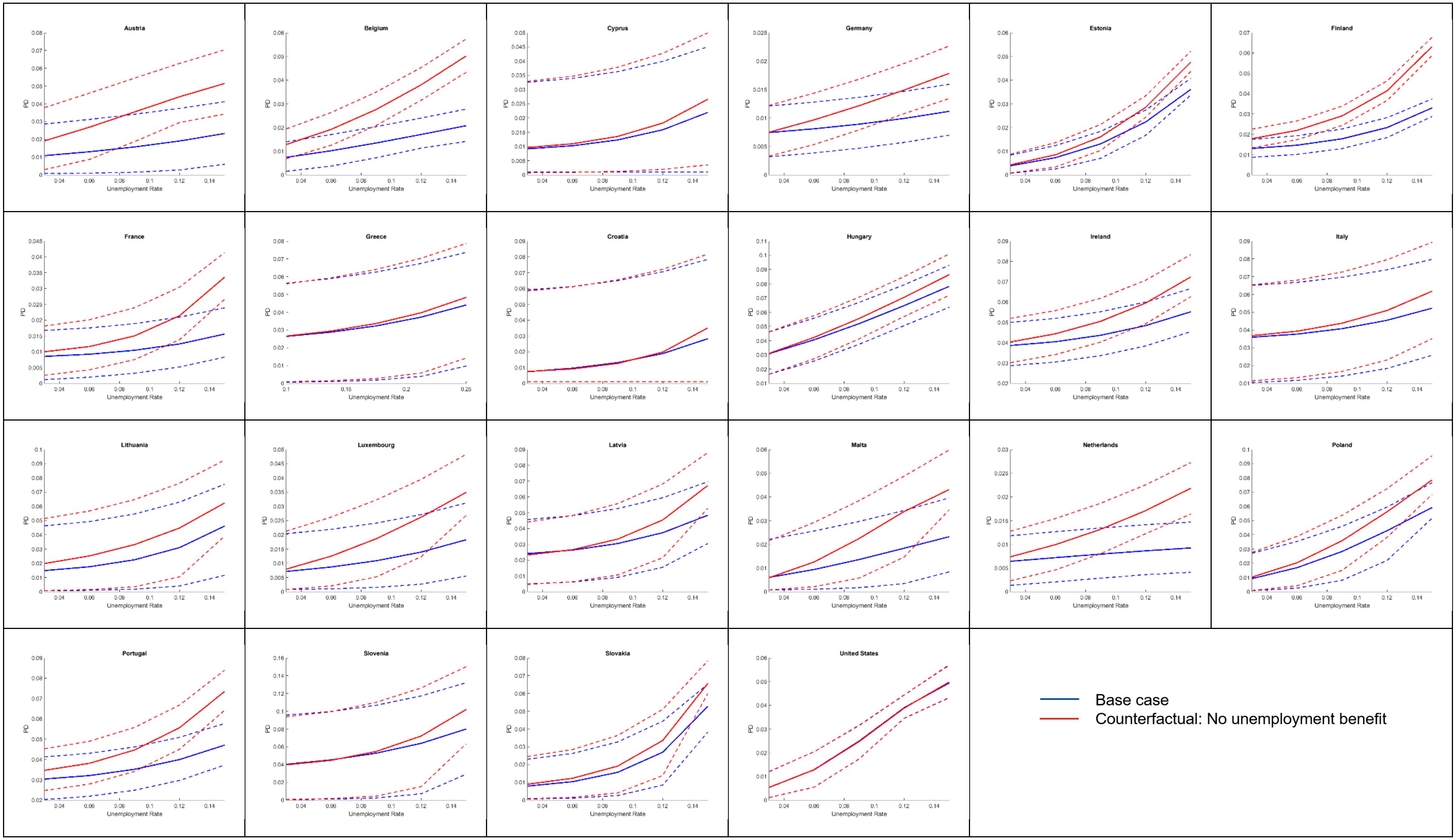
Figure 6. Explaining Cross-Country Heterogeneity of PD Sensitivities



Note: The scatter plots relate the average sensitivities of PDs (as displayed in Figure 5) to the share of variable rate debt (left) and gross wage replacement rates (right).

A counterfactual simulation was run to assess the unemployment rate dependence of PDs under the hypothetical assumption of "no unemployment benefit" being available for individuals who become unemployed during the simulation (Figure 7). Such a simulation reveals how relevant the design of unemployment support programs is for the PD-employment dependency. In numerous countries, the difference is visible, most notably so, for example, in the Netherlands, Portugal, France, and Ireland. These are the countries with comparably high wage replacement rates (Figure 6). Countries such as the US, Hungary, and Greece, on the other hand, are examples of countries with low replacement rates, for which the presence of the less generous income support hence makes less of a difference.

Figure 7. PD-Unemployment Rate Dependence under "No Unemployment Benefit" Counterfactual



Note: The figure illustrates the country-specific changes in mortgage PDs' dependence on unemployment rates when considering the counterfactual of "no unemployment benefit." See text for details.

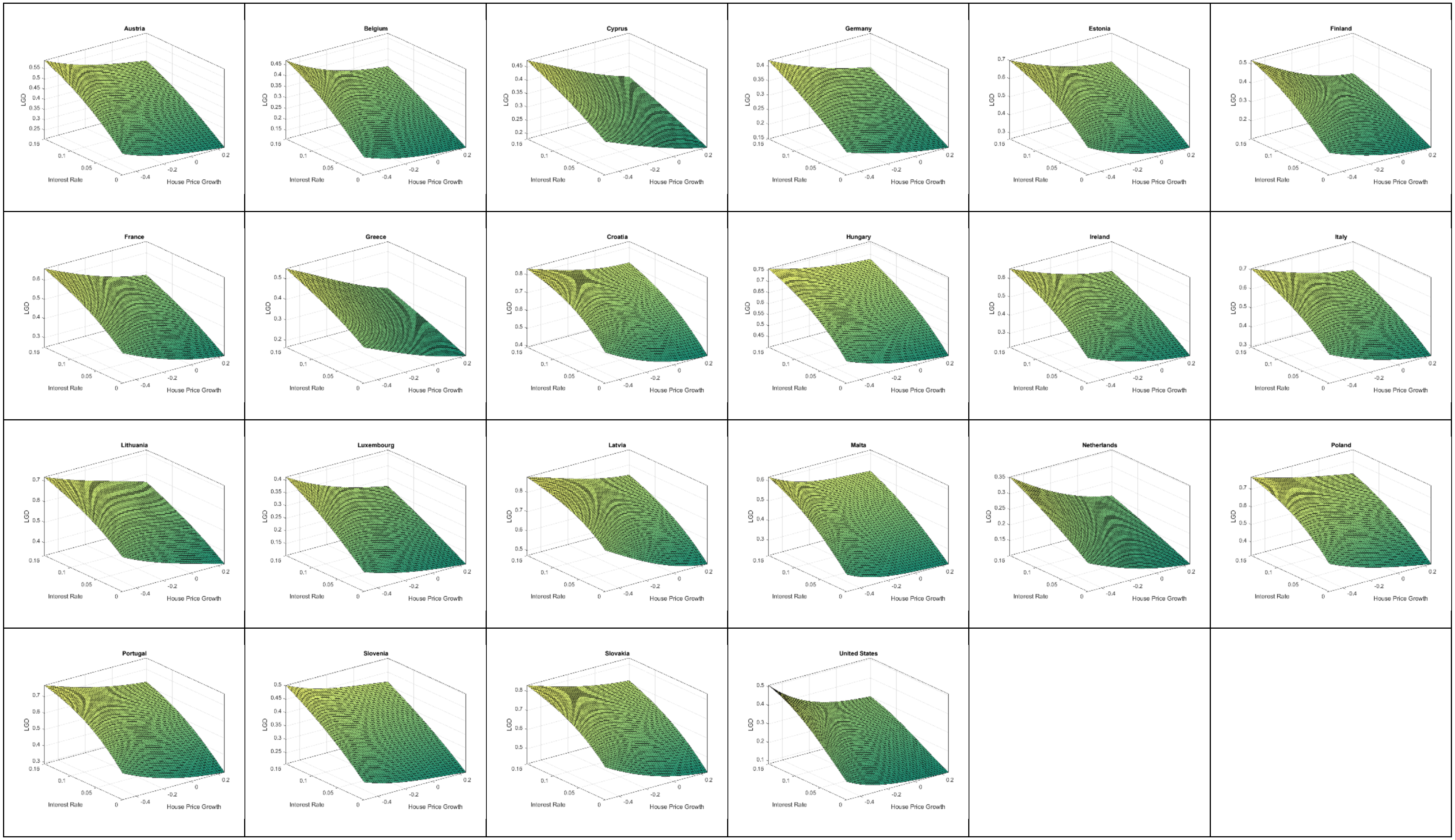
B. Drivers of Mortgage LGDs

Figure 8 shows the LGD simulation results. They are conditional on the grids for house price growth and interest rates. The fact that the interest rate sensitivity is visible reflects that they were here simulated under the "economic mode." Under the "accounting mode," the dependence on interest rates would be absent by design.

The average sensitivities of LGDs to their drivers are more homogeneous across countries compared with those of PDs. Figure 9 shows the average sensitivities, disregarding again any nonlinearities in the underlying relationships.

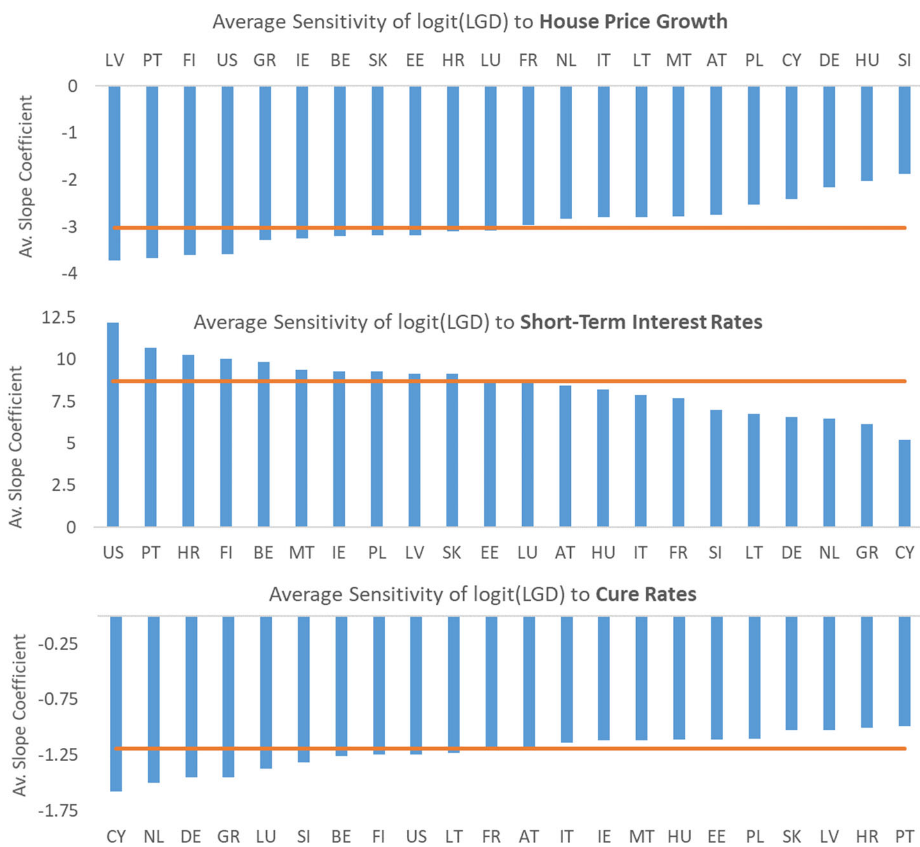
The sensitivity of LGDs to future house price drops is driven to a notable extent by current LTVs (Figure 10). The current LTV measure can be interpreted as a "distance to negative equity" metric. The dependence as shown in Figure 10 confirms the importance of initial conditions regarding current LTVs. The U.S. and the Netherlands stand out as those on the right side of the scatter plot that have high current LTVs as of 2017, which explains their larger LGD-house price growth dependency.

Figure 8. Dependence of Mortgage LGDs on House Price Growth and Interest Rates (Economic LGD Mode, Ceteris Paribus Shifts)



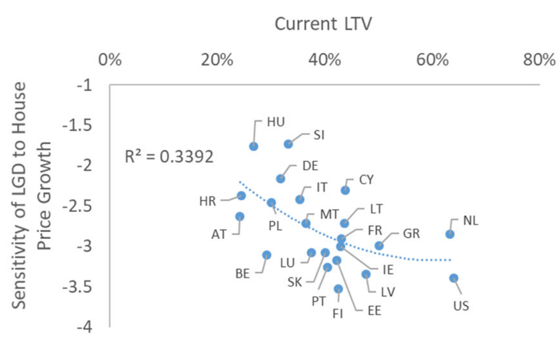
Note: The figures visualize the dependence of household mortgage LGDs on interest rates and house price growth. All other relevant drivers for the LGDs are held constant for the derivation of this trivariate dependence from the structural simulation model. See text for details.

Figure 9. Average Sensitivities of LGDs to Their Drivers



Note: The average sensitivities are obtained by regressing the logit-transformed LGD responses for all countries (resulting from the microsimulation) on the respective grids of the drivers. Such grids were defined using a common range across countries. Orange: median across countries.

Figure 10. Explaining Cross-Country Heterogeneity of LGD Sensitivities



Note: The scatter plot relates the average sensitivities of LGDs to house price growth (as displayed at the top of Figure 9) to population-level current LTV (median across underlying mortgage-holding households).

C. Bridge Equations

The nonlinear bridge equations for PDs and LGDs capture the relationships to their underlying structural drivers from the microsimulation. Second-order polynomials were estimated on the microsimulation outcomes, considering the grids for all relevant macro-financial drivers (Table 5).

The PD-house price growth dependence has been estimated and can be switched on if needed. For countries where strategic default incentives are expected to matter, such as for the US, the house price growth dependence can be switched on. For the countries where they may not matter (most of the European countries), these PD-house price growth relationships are *hypothetical* in the sense that they tell how strong that dependence *would be* if such countries were closer to a no-recourse system.

Table 5. Mortgage PD and LGD Equations Based on Microsimulation Outcomes

	PD Polynomial Coefficients									LGD Polynomial Coefficients (Economic Mode)						
	URX	URX^2	IR	IR^2	CPG	CPG^2	SPG	SPG^2	HPG	HPG	HPG^2	CU	CU^2	IR	IR^2	
AT	5.83	3.51	42.94	-143.15	-2.12	5.30	0.00	0.00	-5.99	-2.35	1.59	-0.91	-0.67	12.94	-30.06	AT
BE	12.78	-22.67	17.25	-42.23	-5.81	14.52	0.00	0.00	-8.22	-2.64	2.22	-0.97	-0.72	16.22	-42.43	BE
CY	0.00	40.97	36.76	-122.54	-8.07	-29.45	-0.03	-0.03	-7.79	-2.42	-0.05	-1.28	-0.74	6.78	-10.53	CY
DE	2.27	6.34	0.63	17.80	-2.31	-0.90	0.00	0.00	-7.41	-1.93	0.91	-1.14	-0.78	9.17	-17.32	DE
EE	23.89	-27.56	41.53	-138.44	-5.55	13.87	-1.23	2.46	-8.97	-2.69	1.91	-0.85	-0.64	13.67	-32.47	EE
FI	0.00	43.98	37.93	-126.44	-12.90	2.76	-0.14	0.21	-8.69	-3.70	1.20	-0.94	-0.77	16.65	-44.13	FI
FR	0.14	27.49	3.07	-7.05	-4.52	-22.60	-0.13	-0.03	-8.39	-2.62	1.36	-0.95	-0.62	11.26	-23.88	FR
GR	0.00	10.11	35.42	-118.08	-14.80	-20.05	-0.03	0.06	-7.42	-3.38	-0.43	-1.14	-0.78	8.30	-14.31	GR
HR	6.48	27.41	19.84	-17.46	-17.29	43.23	0.00	0.00	-3.92	-2.51	2.35	-0.79	-0.53	16.77	-43.26	HR
HU	10.86	-14.96	17.39	-57.97	-4.65	-15.19	-0.05	0.10	-3.24	-1.57	1.80	-0.87	-0.59	12.15	-26.13	HU
IE	0.15	16.56	12.34	-15.02	-2.05	2.01	-0.01	-0.01	-4.47	-2.94	1.24	-0.85	-0.66	14.86	-37.26	IE
IT	0.00	18.13	14.47	-20.53	-9.47	-47.33	0.00	0.00	-4.13	-2.39	1.59	-0.88	-0.64	11.61	-24.85	IT
LT	1.64	44.86	38.59	-128.63	-8.43	-42.13	-0.05	0.10	-4.34	-2.72	0.26	-0.97	-0.64	9.30	-16.94	LT
LU	5.53	13.46	47.02	-145.20	-8.16	-4.97	0.00	0.00	-7.94	-2.83	0.99	-1.04	-0.83	13.24	-30.78	LU
LV	0.00	33.40	24.16	-80.53	-4.88	-24.40	0.00	0.00	-7.53	-3.38	1.36	-0.82	-0.52	13.82	-31.20	LV
MT	18.14	-37.69	40.13	-106.01	-13.64	32.79	-0.02	-0.02	-9.00	-1.92	3.45	-0.86	-0.64	15.08	-38.13	MT
NL	4.59	-8.46	45.18	-150.60	-3.17	-0.49	-0.02	-0.02	-8.65	-2.71	0.48	-1.17	-0.81	9.31	-18.88	NL
PL	25.24	-51.64	69.63	-232.09	-15.43	-4.34	0.00	0.00	-6.20	-2.10	1.69	-0.88	-0.56	14.56	-35.28	PL
PT	0.00	21.08	25.06	-75.31	-4.28	-17.02	-0.01	0.02	-4.69	-3.34	1.30	-0.79	-0.50	18.24	-50.28	PT
SI	2.02	22.45	19.10	-52.25	-8.70	-43.50	-0.74	-0.74	-2.44	-1.43	1.78	-1.01	-0.76	9.93	-19.60	SI
SK	2.10	78.44	39.74	-132.46	-16.04	0.63	0.00	0.00	-7.38	-2.70	1.94	-0.81	-0.53	13.95	-32.17	SK
US	40.33	-118.84	6.44	11.09	-13.93	22.27	-0.51	0.65	-9.28	-2.66	3.71	-0.95	-0.74	22.36	-67.83	US

Note: The second-order polynomial regression estimates were obtained by regressing the logit-transformed PDs and LGDs resulting from the microsimulation (aggregated to population level using principal exposures for weighting) to their structural drivers that were varied along self-defined grids. URX: unemployment rate. IR: short-term interest rate. CPG: compensation per employee growth (natural log (LN) year-over-year (YoY)). SPG: stock price growth (LN YoY). HPG: house price growth (LN period-over-period). CU: cure rate.

D. Benchmark Analysis and Back-Testing

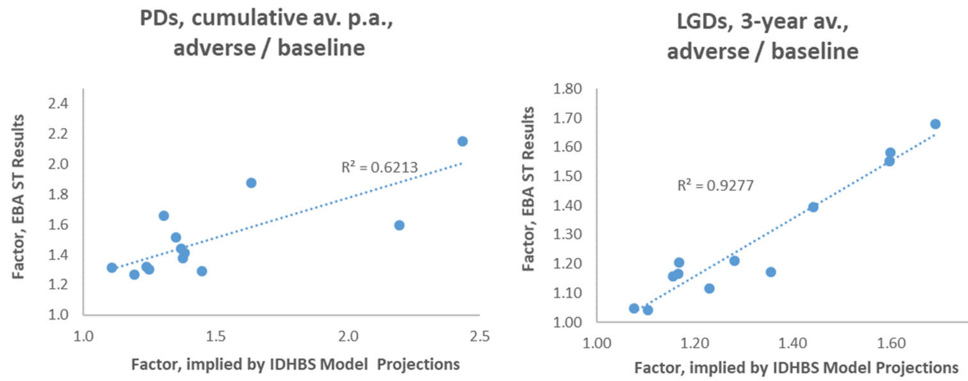
A first benchmark for judging the model-based PD and LGD estimates in relation to their drivers was derived from the EBA/ECB/SSM Stress Test (2018).[17] Locational mortgage default rates and LGDs (proxied by mortgage portfolio coverage ratios) were derived for the countries to which the EBA sample of banks have exposures and reported their bank-specific scenario conditional forecasts. These impacts were processed along with the EBA baseline and adverse scenarios for unemployment rates, house price growth, short-term interest rates, and stock price growth. The LGD module was run under the accounting mode since the aim was to compare the LGD projections to banks' LGDs, which, too, compute them subject to an accounting regime.

The benchmark analysis involves multivariate macro-financial scenarios instead of single-factor grids. The EBA/ECB/SSM Stress Test scenarios as of 2018 are used to feed the

[17] The EBA stress test of 2018 involved 48 banks from 15 EU and EEA countries. The scenario covered all 28 EU countries and selected countries from the rest of the world, in order for the banks from the 15 countries to model the impacts on their loan portfolios in a locational manner. More details can be found under https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2018.

microsimulation. Figure 11 shows the results. A broad correspondence can be seen. It should be kept in mind that the comparison here is between two sets of models, the banks' models that implied their own scenario-conditional response, versus the enhanced IDHBS model outcomes here.

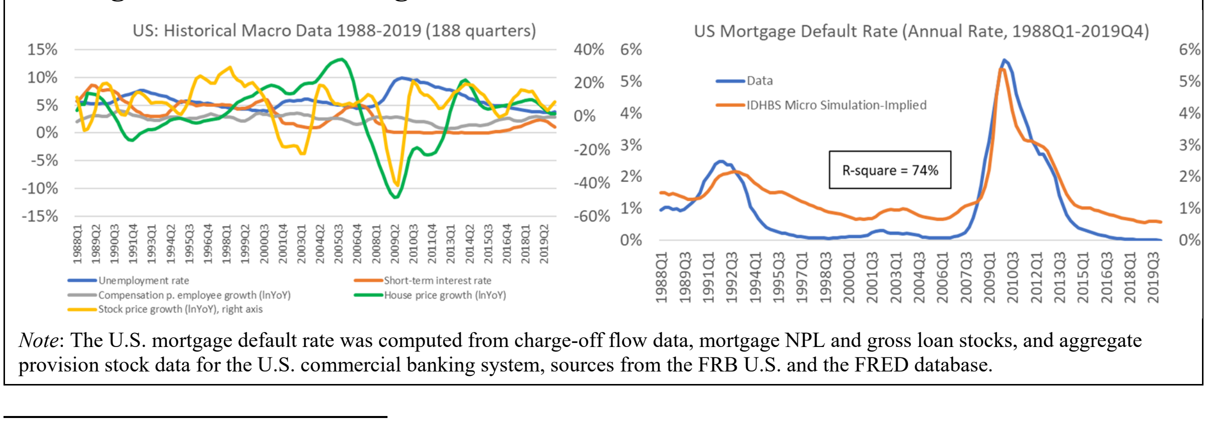
Figure 11. Scenario-Conditional Mortgage PDs and LGDs—Microsimulation vs. Benchmark Informed by EBA/ECB/SSM Stress Test 2018



Note: The dots reflect 13 countries, to which the EBA stress test sample of European banks is exposed.

A back-testing analysis conducted for the U.S. suggests a reasonable historical predictive performance. The microsimulation was run for a 32-year sample (1988Q1–2019Q4, 188 quarters), based on the realized history of the relevant macro-financial variables. The strength of the strategic default incentive was set judgmentally to 50 percent, that is, when a household would receive a default flag specifically due to the negative equity element of the default criterion in eq. (5) during the simulation, then a strategic default would result with a probability of 50 percent. Figure 12 shows the macrodata history (left) and the outcome of the historical simulation (right). The full-sample R-square equals 74 percent. The predictive accuracy during the global financial crisis appears satisfactory. The 1990–91 recession is not so well captured, which is likely because only the 2017 microdata wave was employed for the historical simulation. Using the historical PSID data waves from the past may improve the historical predictive performance further.[18]

Figure 12. Back-Testing Historical PDs from the Microsimulation for the US



Note: The U.S. mortgage default rate was computed from charge-off flow data, mortgage NPL and gross loan stocks, and aggregate provision stock data for the U.S. commercial banking system, sources from the FRB U.S. and the FRED database.

[18] An estimating regression equation with logit PDs from Figure 12 (blue line) on the left hand-side, and all macro-financial variables from the left side of Figure 12 on the equation's right side results in an R-square of 67 percent (less than 74 percent from the structural model). We do not wish to overemphasize such comparison, however, because the structural model was not re-run on all past waves of the micro data; though this would likely further improve the structural model's performance beyond the R-square of 74 percent.

V. Scenario-Conditional Forecasting and Fiscal Policy Analysis Amid COVID-19

Three scenarios are considered for the policy analysis (Table 6): (1) a no-pandemic baseline counterfactual, equated with the December 2019 IMF WEO for all countries; (2) an adverse scenario, taken from the October 2020 WEO, which we use instead as a rough proxy of an explicit counterfactual of a pandemic without any policy support measures being in place; and (3) a pandemic baseline scenario, including an account for all relevant policy responses, which, too, was taken from the IMF's October 2020 WEO. The latter is split into two components: the first one considers translating the macro scenarios via the microsimulation while the second one, in addition, reflects some features of the COVID-19 policies in the microsimulation. The scenario simulation horizon is three years (2020–22). In all cases, the LGDs were computed under the accounting mode. Figure 13 shows the scenario features of all relevant macro-financial variables. The house price growth paths are not overly adverse during the pandemic scenarios, which is in line with the observed data throughout much of the year 2020, according to which house prices have been rather stable in many countries.

Table 6. Overview—Scenarios

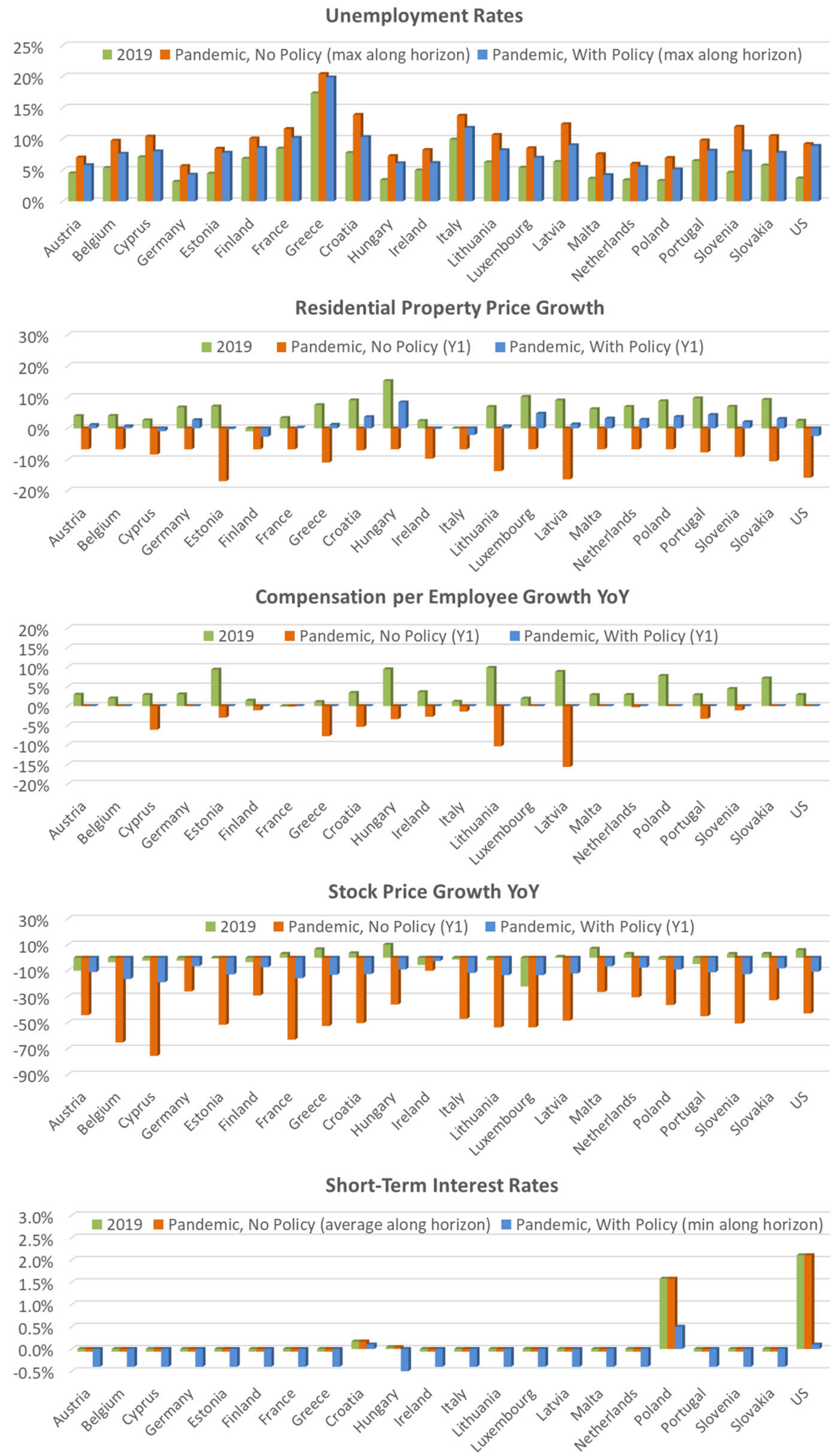
No Pandemic	WEO Dec-2019
Pandemic, No Policies	Adverse down-side scenario without policies
Pandemic, Policies refl. in Macro	WEO Oct-2020
Pandemic, Policies refl. in Macro + Micro	WEO Oct-2020 and moratoria reflected in micro simulation

Source: Authors.

The scenario simulation with policies reflected at the micro level takes account of the country-specific durations of household debt moratoria. Figure 14 shows the durations in months. In France and the US, supervisors/the government did not announce explicit moratoria. A duration of six months has nonetheless been assumed for the two countries, to reflect the fact that banks considered payment moratoria for their borrowers even in the absence of state- or supervisory-instructed moratoria. Section VII discusses some related matters.

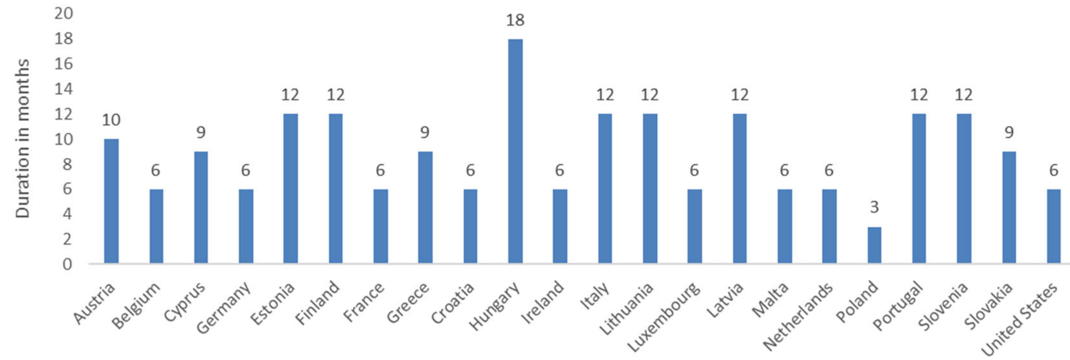
The simulated mortgage PDs, LGDs, and loss rates suggest that household sector-oriented policies can have notable mitigating effects (Figure 15 and Table 7). The most notable uncertainty surrounds the adverse-no-policy response scenario, as it was a "proxy" calibration and hence does not reflect in all detail the assumption of all support policies being switched off. Somewhat less emphasis should therefore lie on it. This caveat notwithstanding, the impact of the policies in a broad sense is visible and economically relevant.

Figure 13. Macro-Financial Scenarios



Sources: IMF WEO October 2020 and author calculations.

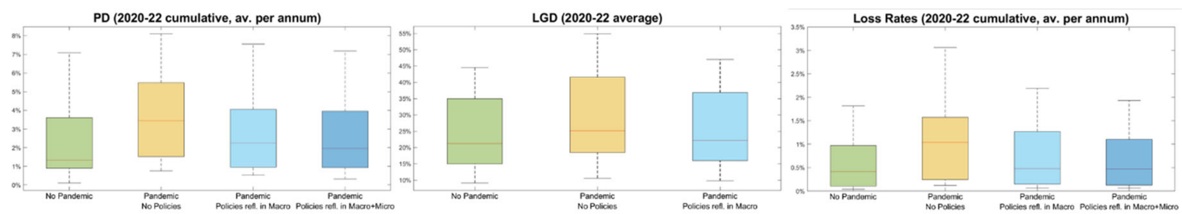
Figure 14. Duration of Household Sector Moratoria (in months)



Source: Fiscal and bank supervisory authorities of the respective countries.

Figure 15. Scenario-Conditional and Policy Counterfactual Mortgage PDs and LGDs

Median/75th Perc. Over 22 Countries	Scenario							
	No Pandemic		Pandemic, Adverse		Pandemic, Policies refl. in Macro		Pandemic, Policies Reflected	
	q=0.5	q=0.75	q=0.5	q=0.75	q=0.5	q=0.75	q=0.5	q=0.75
PD (3-year cumul, av.p.a.)	1.3%	3.6%	3.4%	5.5%	2.2%	4.0%	2.0%	3.9%
LGD (3-year av.)	21.2%	33.7%	25.1%	39.1%	22.2%	35.2%	22.2%	35.2%
Loss Rate (3-year cumul., av.p.a)	0.41%	0.94%	1.04%	1.55%	0.48%	1.26%	0.48%	1.10%



Note: For the LGD impacts, there is no distinction between "pandemic, policies reflected in macro" and "pandemic, policies reflected," because reflecting them entails here only one step, that is, whereby house price growth exerts its impact on LGDs.

Table 7. Scenario-Conditional and Policy Counterfactual Impact on Bank Capital Ratios

Median/25th perc. over 22 Countries; Deviation from No Pandemic Counterfactual	Scenario			
	Pandemic, Adverse		Pandemic, Policies Reflected	
	q=0.25	q=0.5	q=0.25	q=0.5
Loan Loss Contr. to ΔCAPR	-0.58 pp	-0.25 pp	-0.12 pp	-0.05 pp
ΔRWA Contr. to ΔCAPR	-0.54 pp	-0.25 pp	-0.10 pp	-0.04 pp
Δ Capital Ratio	**-1.21 pp**	**-0.46 pp**	**-0.19 pp**	**-0.14 pp**

Note: The impacts reported in the table are medians and 25th percentiles across the underlying 22 countries.

VI. Discussion: Debt Moratoria and Guarantees for the Household Sector

The rationale for private sector debt moratoria lies in the expectation that borrowers experience payment difficulties *due only to temporary illiquidity*, and not to beyond-short-term insolvency. Allowing illiquid borrowers to temporarily pause paying interest and amortizing principal debt can be net beneficial for banks, since the cost of letting such loans default and having to seize and sell the collateral may exceed the expected remaining lifetime interest income upon the borrower resuming the payments after a moratorium's end. In a pandemic with great economy-wide scope such as COVID-19, the volume of defaulting debt contracts and related collateral seizure could become very significant if banks were not to consider moratoria. It would likely entail strong second-round feedback and amplification effects, including a considerable drag on house prices and hence rising LGDs.

Even in the absence of state- or supervisory-led moratoria, banks engage in granting payment moratoria for such expected (and highly uncertain) cost benefit-related reasons. The reasons it can nonetheless be useful to consider state- or oversight institution-led moratoria include: (1) easing the decision process for banks by applying moratoria in a broader manner for whole portfolios instead of requiring more costly assessments loan by loan; and (2) reducing an otherwise significant uncertainty as well as potential burden on the side of borrowers in terms of the need for renegotiating the loan contract terms. Moreover, it is useful for regulators to provide guidance in terms of the accounting treatment of loans under moratoria.

Guidance regarding the accounting treatment (under IFRS 9) of debt under moratoria was issued in many jurisdictions. IFRS 9—the prevalent accounting regime in place for about 90 percent of countries worldwide (having replaced the previous IFRS accounting standard for banks—IAS 39—in January 2018)—leaves it to banks to decide what stage-migration criteria to employ, though it provides guidance (paragraph B5.5.17 in IASB 2014). Among the suggested criteria (16 in total), one of them considers the "…expected breach of contract that may lead to covenant waivers or amendments, interest payment holidays, interest rate step-ups, requiring additional collateral or guarantees, or other changes to the contractual framework." In line with this guidance, many banks are known to have included a forbearance (modification) event in their list of triggers for Stage 2 before the pandemic. This notwithstanding, the IFRS 9 framework otherwise suggests that modification gains and losses should simply be recorded and the modified loan exposures be placed in the stage that best represents its risk dynamics since origination (paragraphs 5.4.3, B5.5.2, and B5.5.25-27 in IASB 2014). The additional guidance, as published by the IASB, the EBA, the ECB, and others, just offers clarity in that banks should "look through" the pandemic shock and should not "stick blindly" to their previously self-set criteria in that context.[19] Still, banks are supposed to conduct a risk assessment with a debt's lifetime horizon, to the best of their ability, to also *not rule out* that loans under moratoria can be placed in Stage 2 and be provisioned accordingly. A dedicated data collection compiled by the EBA for European banks suggests, in fact, that lots of banks placed a larger amount of loans under moratoria in Stage 2, implying higher provisioning requirements (EBA 2020b).

A policy that governments can consider is an interest income support, at least of a partial kind, for banks. The fact that principal debt is not being repaid temporarily may not harm banks as much in the short term, as it has hardly any P&L effect, except for the release of provisions as a result of repayment under IFRS 9 (and CECL in the US) for performing credit exposures. Apart from that, it may only imply somewhat less new bank lending potential, as

[19] IASB (2020) is the IASB's own guidance. See also EBA (2020a) for the EBA's additional guidance. See Bank for International Settlements (BIS) (2020) for the guidance from a regulatory perspective and the suggested additional transitional arrangements related to IFRS 9 as a response to the pandemic. See Regulation (EU) (2020) for the EU's "CRR Quick Fix."

putting repayment on hold implies *more leverage than otherwise*. From a P&L accounting viewpoint, interest payments keep accruing through banks' P&L and contributing to bank capitalization, even if interest pauses from a cash-inflow perspective.[20] Yet, it is worth considering a state support for covering an annuity's interest portion so that it does not accrue *for borrowers*. Accrued interest otherwise becomes due at a moratorium's end, and it then depends on how banks redesign the loan contracts, ideally in a way that the additional repayment burden does not imply defaults later. Italy is an example where interest has been partially covered by the state during the time of the moratorium.[21] There is a tradeoff for the government insofar as covering the *full* accruing interest may not be financially optimal, because a portion of the borrower population would actually be able to pay the interest themselves. The choice depends on the government's preference and its assessment of the duration and severity of the economic disruption caused by the pandemic.

Conditionality criteria should be and were being considered, to let only borrowers in need qualify. Besides basic criteria such as job loss and material income loss, other criteria include available cash and cash-equivalent savings thresholds above which debtors do not qualify for moratoria, as they would be able to service their debt by first depleting their savings. This was the case in Belgium, for example, where such a threshold was set to EUR 25,000.

Guarantees for household sector debt impact banks primarily by lowering LGDs. Although the LGD for a loan as such remains unaffected in economic terms, a loss is covered if the borrower defaults on the loan. A secondary positive impact (via borrower PDs) may arise through loan interest rates being lower than otherwise, because banks may price the presence of guarantees in. This is a mechanism that is more relevant for borrowing firms in need of continuous rollover of their working capital loans (that is, for new loans). It also impacts household loans through new lending as well as through outstanding variable rate contracts. Guarantee schemes should be designed in a way to not unduly stimulate demand for new housing beyond sustainable levels, as that would risk contributing to the build-up of house price overvaluation.

There is an interaction between support measures for firms and those for households. Supporting firms through wage subsidies by relaxing rules that would otherwise constrain part-time work, or by providing working capital loans at small or zero interest terms, eventually also helps households and employees. This is because the chance of job loss and dropping income would decrease.

VII. Conclusions

A structural micro-macro simulation model has been employed to uncover the drivers of PDs and LGDs for 21 EU countries and the US. The simulations based on the extended IDHBS model (GP 2017) have revealed the dependence of mortgage PDs and LGDs on their structural drivers, including, in particular, unemployment and interest rates for what concerns defaults, and house price dynamics for what concerns LGDs. The model extensions compared

[20] If interest payment flows pause for too long, that is, if the pandemic were to last longer, then it might become increasingly apparent that the accrued interest that was booked through the P&L would have inflated capital ratios too much. This is the case when an assessment of short-term illiquidity would increasingly turn to beyond-short-term insolvency, which would mean that the accrued interest would have to be unwound, as expected to not be paid back due to eventual borrower default.

[21] For details of the Italian government's Decree of March 2020 see: https://www.gazzettaufficiale.it/eli/id/2020/03/17/20G00034/sg.

with the original IDHBS model include the addition of a realistic nonlinear debt repayment mechanism, the inclusion of debt-holding pensioners, an interest income module, and a refined LGD module. In addition, we estimate nonlinear regressions linking the microsimulation-implied PDs and LGDs to their macro-financial drivers. This is convenient for scenario-conditional forecasting, as they can be used to that end without needing to conduct the microsimulation. When counterfactual policy assumptions (fiscal, monetary, macroprudential) are to be combined with macro scenarios, the microsimulation ought to be run.

The model can be integrated in larger scale structural and semi-structural macro-financial models. The microsimulation model captures the dependence of household risk metrics on their macro-financial environment. The assumption is that the macro scenarios currently fed through the model capture the endogeneity of household sector and wider macroeconomic dynamics jointly. Whatever higher-level capture of the dependence of the feedback from household sector risk to macro dynamics can be replaced when embedding the microsimulation model therein.

The cross-country heterogeneity of the sensitivities of PDs and LGDs to their macroeconomic drivers resulting from the model can be well explained by structural differences in labor and credit markets. The dependence of PDs on employment dynamics, for example, is tighter in countries with low unemployment benefits, such as the US. The dependence of PDs on interest rates is stronger in countries with higher variables rate contract shares, such as the Netherlands. Differences in cash or cash-equivalent savings stocks across countries compound these dependencies. LGDs are particularly susceptible to house price changes in countries with high initial LTVs, such as the US, the Netherlands, and several Central and East European countries. Such conclusions are all conditional on market structures as of the current survey dates, that is, as of 2017.

The model-based PD and LGD sensitivities were benchmarked against a sample of European banks' own model-based PD and LGD forecasts (EBA 2018 Stress Test), and via a back-testing exercise for the U.S. mortgage PDs for a 32-year historical sample. A notable level of consistence between the microsimulation results and the PD and LGD estimates from EU banks for their mortgage portfolios has been found. The historical back-testing exercise for the U.S. suggests that conditional on realized historical macro developments, the model predicts well the default rate level in the U.S. ensuing through the 2007–09 recession.

The model provides a new way to conduct policy counterfactual analyses. The analysis of macroprudential policies was illustrated in GP (2017) and Jurča et al. (2020). In the present paper, the focus is on borrower support measures as deployed in response to the COVID-19 pandemic. The model can help inform which labor or credit market features matter in a cross-country comparative manner, and then help quantify policy counterfactual impacts, as illustrated for household debt moratoria in this paper. It can be used to inform how sizable a wage subsidy or cash grants should be for a given population, to achieve a certain target level of PDs that policymakers wish not to exceed.

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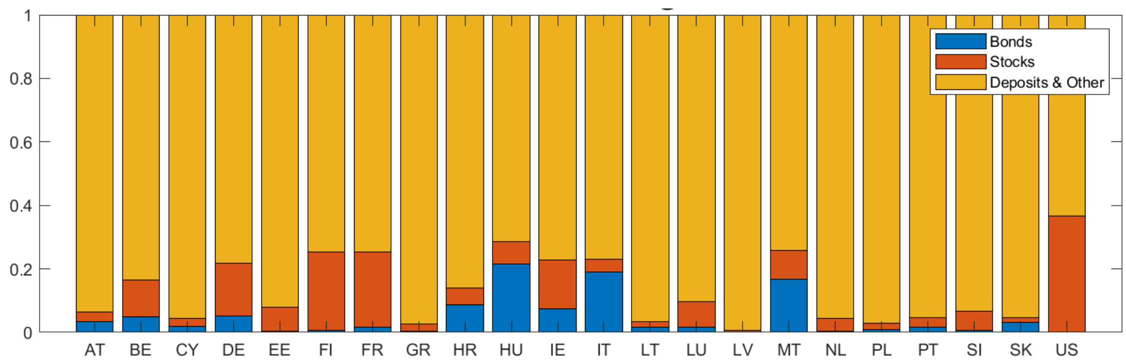
ANNEX 1. MICRODATA CHARACTERISTICS

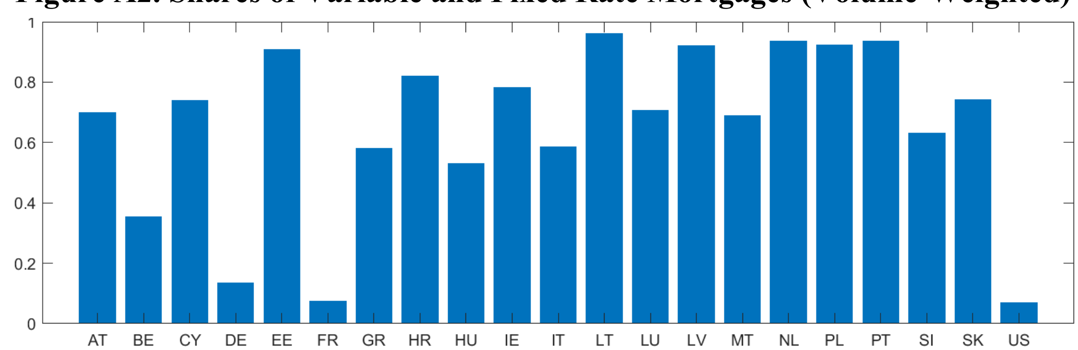
Figures A1–A6 summarize some basic characteristics of the microdata for the EU (HFCS data) and the U.S. (PSID data).

Figure A1. Shares of Bond and Stock Holdings in Households' Total Financial Assets



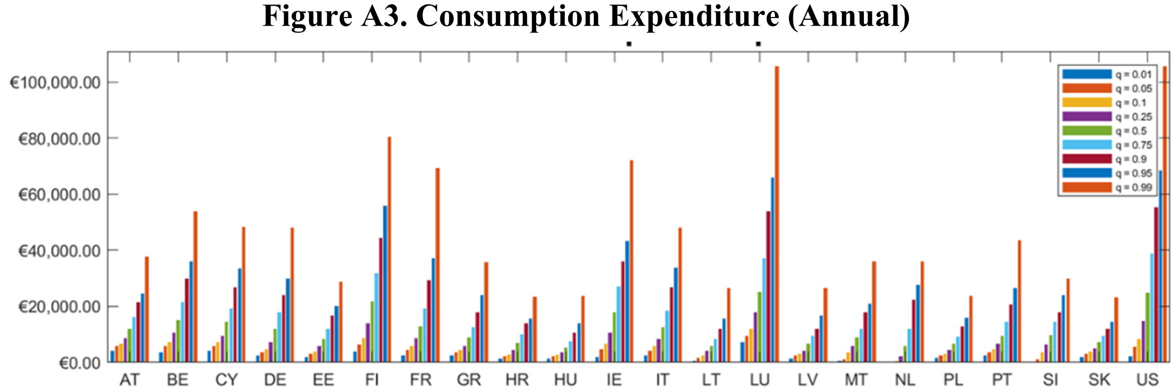
Note: For the U.S., bond holdings of households are not separately reported but contained in the aggregate, which here is called "Deposits & Other." The chart shows the shares for 21 EU countries and the U.S.

Figure A2. Shares of Variable and Fixed Rate Mortgages (Volume-Weighted)



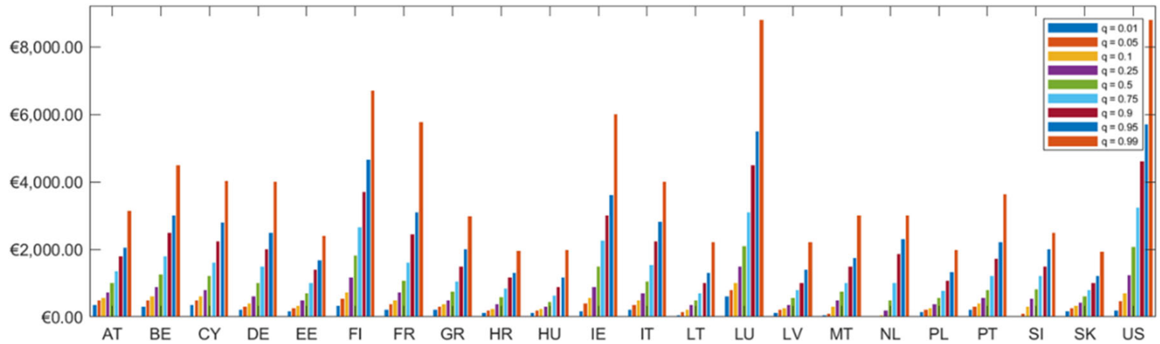
Note: The chart shows the variable rate mortgage shares for 20 EU countries and the U.S. (Finland is excluded because the HFCS microdata do not report the contract type for Finish households).

Figure A3. Consumption Expenditure (Annual)



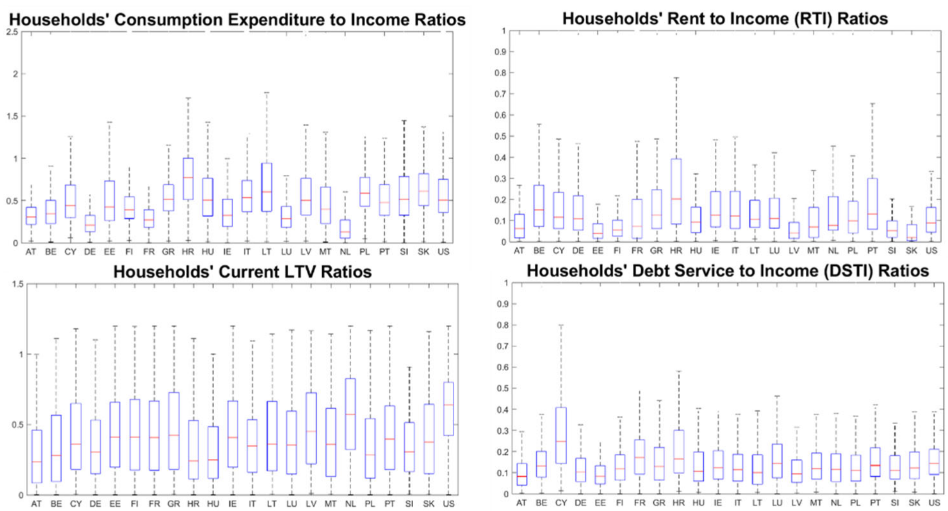
Note: The underlying microdata are as of 2017 for all countries. Microdata for the U.S. converted from USD to EUR (at av. 2017 USD-EUR exchange rate).

Figure A4. Consumption Expenditure (Monthly)



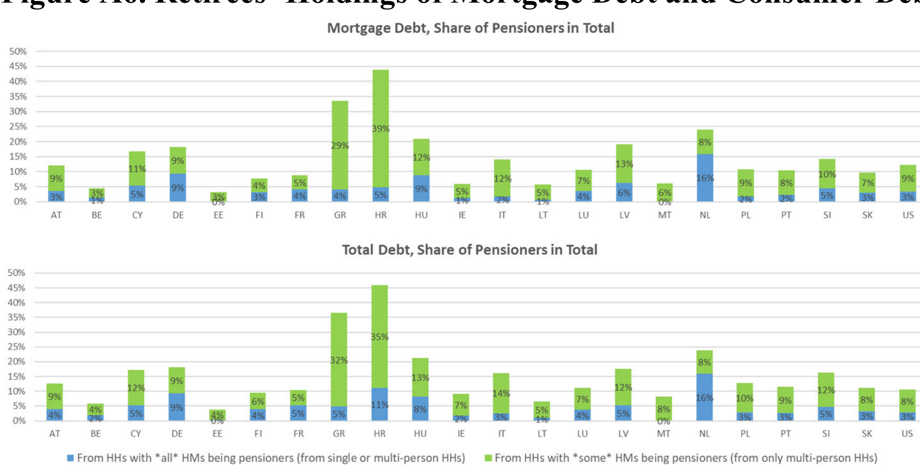
Note: The underlying microdata are as of 2017 for all countries. Micro data for the U.S. were converted from USD to EUR (at av. 2017 USD-EUR exchange rate).

Figure A5. Consumption Expenditure to Income, Rent to Income, LTVs, and DSTIs



Note: The box plots are based on the underlying household level data for the respective 22 countries. Red lines are medians. The whiskers extend to minima and maxima (after exclusion of outliers).

Figure A6. Retirees' Holdings of Mortgage Debt and Consumer Debt



Note: The shares of retirees' debt holdings are based on the 2017 survey waves of the HFCS and the PSID.

ANNEX 2. MAPPING HFCS AND PSID DATA INTO THE MODEL

Table A1 summarizes how the data from the HFCS and PSID databases were mapped into the IDHBS micro-macro simulation model. Tables A2–A4 show the recoding of the labor status, the marital status, and the education variables for their use in the model.

Table A1. Microdata Mapping into the IDHBS Simulation Model

		Model Variable		Variable Code in Micro Data & Transformations	
				HFCS (EU21)	PSID (US)
HH-Level	Assets	H	Current value of house	DA1110	ER66031
		TFA	Total financial assets (incl. cash, stocks, bonds, pensions, life insurance)	DA2100 - DA2104 (value of business) - DA2107 (money owed to others)	ER71435 + ER67847 + ER67819 + ER71445
		B	Current market value of bonds	DA2103	Incl. in TFA, cannot be separated
		S	Current market value of stocks	DA2105	ER71445
	Liabilities	D^M	Outstanding balance of mortgage debt	DL1100	ER66051 + ER66072
		D^{NM}	Outstanding balance of non-mortgage debt	DL1200	ER71459 + ER71463 + ER71467 + ER71471 + ER71475 + ER71480
	Income Flows	I	Household income total, quarterly, gross of tax (used only for calculation of DSTI and DTI ratios for MPRU policy exp.; labor income, pensions, and unemployment benefit are used and modeled at HH member-level)	DI2000 / 4	ER71426 / 4, if not available then from ER71330 / 4
		RI	Rental income, quarterly	HG0310 / 4	(ER71294 + ER71322) / 4
		OI	Other regular income, quarterly, e.g. child benefit, alimony, etc.	(HG0110 + HG0210) / 4	(ER71351 + ER71353 + ER71381 + ER71383) / 4
	Expense Flows	$A = A^M + A^{NM}$	Annuity for mortgage debt, quarterly	DL2100 * 3	(ER66053 + ER66074) * 3
			Annuity for non-mortgage debt, quarterly	DL2200 * 3	ER71504 / 4 (for car debt only)
		OE	Rental expense, quarterly (needed only if focus is on HHs who rent)	HB2300 * 3	ER71494 / 4
		E	Living expense, excl. annuities and rent, quarterly	DOCOGOOD / 4	(ER71487 + ER71491 - ER71494 - ER71492 + ER71503 - ER71504 + ER71515 + ER71516 + ER71517 + ER71522 + ER71525 + ER71526) / 4
	Other	HH_ID	Household ID	SA0010 (made unique across countries)	ER66002
		HW	Household weight	HW0010	ER71571
		HH_RES	Country of residence	SA0100	Set to "US" for all HHs
		Myear	Year of 1st mortgage origination; for MPRU exp. only	HB1301	ER66060
		MiniDur	Duration of 1st mortgage at origination in years; for MPRU exp. only	HB1601	Generated as 2017 - ER66060 + ER66061
		DType	Rate type of total debt (variable vs. fixed)	DL1110{a,b,c}i	ER66057 (from 1st mortgage)
		i^M	Current interest rate on mortgage debt; if not reported at HH-level, then filled with country-aggregate consumer debt interest rate	W.A. from mortages outstanding (HB170x) and their interest rates (HB190x)	ER66058 (whole number) & ER66059 (after comma)
		i^D	Current interest rate on total debt; if not reported at HH-level, then filled with country-aggregate consumer debt interest rate	Total absolute annual interest flow (DI1412) over total current debt (DL1000)	Mortgage interest rate (above), multiplied by factor that reflects ratio of non-mortgage debt interest rate to mortgage rates
		M^{RES}	Synthetic residual duration of total debt in months (needed for variable rate loans only)	$\text{ceil}(\log(4{*}A./(4{*}A-i^D.{*}(D^M+D^{NM})))./\log((i^D./12)+1))$	
		Etol	Living expenses (excl. Annuities and rent) as share of gross income	E/I	
HM-Level	Income Flows	INC^E	Labor income (gross of tax) from employment or self-employment, public/private pension income (net of tax), quarterly	(PG0110 + PG 0210 + PG0310 + PG0410) / 4	1st HM: ER67046/4 (labor) + ER71337/4 (veteran pension) + ER71339/4 (other pension) // 2nd HM: ER67401/4 + ER71367/4 + ER71369/4
		INC^U	Unemployment benefit, net of tax, quarterly	PG0510 / 4	1st HM: (ER71347 + ER71420)/4 // 2nd HM: (ER71377 + ER71422)/4
	Other	HM_ID	Household member ID	ID	Generated
		HM_HH_map	Household members' household IDs	SA0010	Generated involving ER71560
		HM_RES	Country of residence	SA0100	Set to "US" for all HMs
		LAB	Labor status; see separate table for code mapping	PE0100a	ER66164 // ER66439
		MAR	Marital status; see separate table for code mapping	PA0100	ER66024 (1st HM's status also set for 2nd HM)
		EDU	Level of education; see separate table for code mapping	PA0200	ER70904 // ER70770
		GEN	Gender	RA0200	ER66018 // ER66020
		AGE	Age	RA0300	ER66017 // ER66019
		DF	Nationality / Domestic-foreign indicator	Generated from country of birth (RA0400) and country of residence (SA0100)	Generated from ER70888 (1st HM) and ER70750 (2nd HM)

The labor status mapping in Table A2 is done in a way to compress the numerous categories considered in the HFCS and PSID surveys down to a binary indicator. The categories indicated with a (*) are those that are excluded from the employment status model (Annex 3) but are included in the household member sample for the microsimulation model. For the microdata variable codes corresponding to the variables covered in Tables A2–A4, see Table A1.

TABLE A2. LABOR STATUS RECODING

HFCS			
Original		Modified	
1	Work	1	Employed
2	Sick leave, but w ork	1	Employed
3	Unemployed	2	Unemployed
4	Student	NaN	
5	Retiree	(*)	
6	Disabled	NaN	
7	Military or social service	1	Employed
8	Domestic tasks	(*)	
9	Other	NaN	

PSID				
Original		Mapped to HFCS	Modified	
1	Work	1	1	Employed
2	Sick leave, but w ork	2	1	Employed
3	Unemployed	3	2	Unemployed
4	Retiree	5	(*)	
5	Disabled	4	NaN	
6	Keeping house	8	(*)	
7	Student	4	NaN	
8	Other	9	NaN	
99	DK	9	NaN	

TABLE A3. MARITAL STATUS RECODING

HFCS			
Original		Modified	
1	Single	1	Single
2	Married	2	Married
3	Cons. union (	2	Married
4	Widow ed	2	Married
5	Divorced	1	Single

PSID				
Original		Mapped to HFCS	Modified	
1	Married	2	2	Married
2	Never marrie	1	1	Single
3	Widow ed	4	2	Married
4	Divorced	1	1	Single
5	Separated	5	1	Single
8	DK (0 cases	1	1	Single
9	NA (1 case)	1	1	Single

TABLE A4. EDUCATION STATUS RECODING

HFCS			
Original		Modified	
1	Primary (ISCED1)	1	No university
2	Secondary (ISCED2)	1	degree
3	Upper secondary (ISCED3+4)	1	
5	University (ISCED5+6+7+8)	2	University degree

PSID				
Original		Mapped to HFCS	Modified	
1	yes	5	2	University degree
5	no	1	1	No university
9	DK/NA	1	1	degree
0	inap	1	1	

ANNEX 3. LOGISTIC MODELS FOR HOUSEHOLD MEMBER EMPLOYMENT STATUS

Table A5 presents the logit model estimates for the employment status of individual household members contained in the HFCS (21 EU countries) and the PSID (US). Figure A6 visualizes the estimated unemployment probabilities, along with the country aggregate unemployment rates from the survey databases as of 2017.

Table A5. Logistic Model Estimates for Employment Status

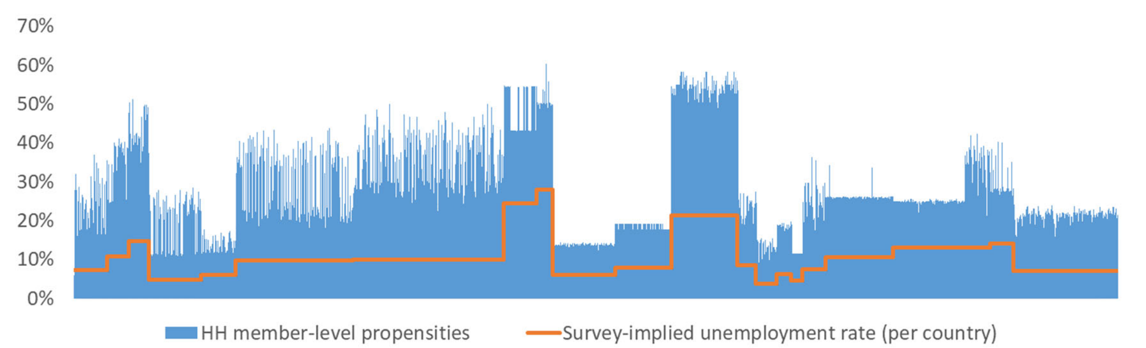
Coefficients	AT	BE	CY	DE	EE	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK	US
Intercept	4.40	2.30	2.49	3.82	2.20	2.51	1.26	1.22	0.92	4.06	3.49	0.85	4.05	2.28	3.37	5.40	4.35	2.84	2.73	3.52	2.50	3.19
Marital status	-1.13	-1.21	-1.30	-1.11	-0.25	-0.87	-0.87	-0.73	-0.58	-0.72	-1.03	-0.70	-0.68	-0.31	-0.70	-0.76	-0.22	-0.83	-0.77	-0.96	-0.69	-1.17
Education	-1.14	-0.85	-0.93	-1.15	-0.79	-0.68	-0.85	-0.65	-0.92	-1.13	-0.90	-0.94	-0.81	-0.84	-1.05	-2.32	-1.00	-1.30	-0.95	-0.98	-1.69	-0.83
Gender	-0.17	-0.03	0.49	-0.12	-0.20	0.00	0.16	0.59	0.57	0.04	-0.12	-0.02	-0.37	0.06	-0.52	0.54	0.52	0.63	0.16	0.51	0.08	-0.25
Dom/Foreign	0.82	0.71	0.37	1.08	0.76	1.10	0.81	0.46	0.42	-0.61	0.09	-0.24	0.07	0.95	0.08	-0.28	0.47	0.39	0.03	0.12	0.65	-0.09
Age	-0.02	0.01	-0.01	-0.01	0.01	-0.01	0.03	0.00	0.01	0.01	0.00	0.04	-0.02	0.03	0.01	0.00	-0.03	0.00	0.00	-0.02	0.01	0.02

P-Values	AT	BE	CY	DE	EE	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK	US
Intercept	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Marital status	0.0%	0.0%	0.0%	0.0%	13.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	21.1%	0.3%	1.0%	21.2%	0.0%	0.0%	0.0%	0.0%	0.0%
Education	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Gender	21.8%	81.0%	0.0%	35.1%	18.5%	99.2%	0.4%	0.0%	0.0%	68.3%	24.6%	79.0%	3.2%	78.8%	2.5%	6.6%	0.1%	0.0%	2.5%	0.0%	51.9%	0.2%
Dom/Foreign	0.0%	0.0%	5.2%	0.0%	0.1%	0.0%	0.0%	0.0%	4.6%	18.7%	47.2%	2.5%	77.3%	0.0%	83.1%	70.3%	1.1%	48.1%	79.5%	68.6%	22.5%	54.6%
Age	0.0%	16.1%	35.3%	13.9%	2.7%	0.0%	0.0%	91.3%	15.0%	2.6%	0.0%	0.0%	0.7%	0.8%	16.5%	0.0%	0.0%	77.4%	41.8%	0.0%	13.6%	0.0%

Stats	AT	BE	CY	DE	EE	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	SI	SK	US
Obs.	3,325	2,194	2,101	5,300	3,497	11,984	15,308	3,333	1,645	6,380	5,728	6,750	1,869	2,104	1,507	1,104	2,343	6,878	7,319	2,568	2,403	10,583
AUROC	0.67	0.69	0.67	0.71	0.64	0.66	0.70	0.61	0.60	0.67	0.67	0.68	0.64	0.70	0.70	0.70	0.68	0.67	0.62	0.65	0.66	0.69

Note: The left-hand side variable is coded as 0 = unemployed, 1 = employed. Marital status: 0 = married, 1 = single. Education: 0 = university degree, 1 = no university degree. Gender: 0 = female, 1 = male. Domestic/foreign indicator: 0 = foreign, 1 = domestic national.

Figure A6. Distribution of Unemployment Probability Estimates, Household Member Level, 22 Countries



Note: Country blocks are collected side by side. At each point where the horizontal line moves to a different level, a new country block starts.

PUBLICATIONS

What Drives Mortgage Default Risk in Europe and the U.S.?
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