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Do macroprudential measures increase inequality? Evidence from the euro area household survey

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Abstract

Borrower-based macroprudential (MP) policies - such as caps on loan-to-value (LTV) ratios and debt-service-to-income (DSTI) limits - contain the build-up of systemic risk by reducing the probability and conditional impact of a crisis. While LTV/DSTI limits can increase inequality at introduction, they can dampen the increase in inequality under adverse macroeconomic conditions. The relative size of these opposing effects is an empirical question. We conduct counterfactual simulations under different macroeconomic and macroprudential policy scenarios using granular income and wealth data from the Households Finance and Consumption Survey (HFCS) for Ireland, Italy, Netherlands and Portugal. Simulation results show that borrower-based measures have a moderate negative welfare impact in terms of wealth inequality and a negligible impact on income inequality.

JEL classification: G21, G28, G51.

Keywords: macroprudential policy, inequality, household debt.

Non-technical Summary

This paper aims to asses the welfare costs and benefits of borrower-based measures in terms of wealth and income inequality. Welfare costs arise if wealth and potentially income inequality increase after the imposition of LTV and DSTI limits compared to the counterfactual without these limits. The benefits of borrower-based measures may occur as a result of a lower probability and conditional impact of a financial crisis. Since unemployment in a recession is higher for low income borrowers, an adverse macroeconomic scenario with borrower-based measure in place may result in a lower increase in income inequality compared to the counterfactual adverse scenario without LTV and DSTI limits in place.

To quantify the size of these costs and benefits, we conduct counterfactual simulations comparing wealth and income inequality under 4 policy scenarios (baseline and adverse scenario, with and without borrower-based measures in place). The paper restricts the scope of the study to four euro area countries: Ireland, Italy, Netherlands and Portugal.

To estimate the benefits of macroprudential measures, we proceed in three steps. First, we use a Bayesian VAR (BVAR) to quantify the macroeconomic impact of a credit crunch conditional on an adverse macroeconomic scenario under different macroprudential policy regimes (i.e. with or without LTV and DSTI limits). In a second step, we match the unemployment and asset price response obtained in the BVAR to household data in order to derive income and wealth distributions under these different policy scenarios. Last, we compute the benefit as the difference in income (wealth) inequality between the adverse scenario without borrower-based macroprudential measures compared to the adverse scenario with these measures in place. The cost is computed in a similar fashion, as the difference in income and wealth inequality between the baseline scenarios with and without the borrower-based measures in place. The only difference to the benefits calculation is that the macroeconomic response is computed conditional on a loan demand shock following the implementation of borrower-based measures.

We use the Gini coefficient of wealth and income as a metric for our cost-benefit calculations. We derive the unconditional net benefit as the difference between the expected values of the Gini coefficient with and without borrower-based measures, taking into account the change in the crisis probability across policy scenarios.

In terms of wealth inequality, the unconditional benefit is negative, ranging from -0.14 percentage points in Italy to -0.58 percentage points in the Netherlands. The negative unconditional benefit implies a net increase in wealth inequality relative to the counterfactual without borrower-based measures. In the case of income inequality, the unconditional benefit of borrower-based measures is marginally positive, ranging from 0.04 percentage points for Italy to 0.16 percentage points for Ireland. These results suggest that the welfare cost of macroprudential regulation in terms of wealth inequality is contained, while the benefit in terms of income inequality is negligible.

1 Introduction

In many advanced economies, home ownership is part of the social contract between policy makers and citizens, acting as a symbol for social inclusion and economic growth. In this sense, the housing finance deregulation in the decade preceding the Great Financial Crisis in the US and UK was meant to act as a redistributive force, potentially reducing wealth and income inequality (Arundel and Ronald (2020), Rajan (2011), p. 35-40). After the bursting of the sub-prime housing bubble in 2008, access to mortgage loans has been tightened in most euro area countries. In this context, macroprudential policies (MP) have been widely used by policy makers due to their ability to address the build-up of asset price bubbles and excessive risk-taking by banks. Some of these measures can target banks, for example countercyclical capital requirements, while others target borrowers, such as the loan-to-value ratio (LTV) or the debt-service-to-income limit (DSTI).[1]

While the main policy objective of MP is to enhance financial stability by increasing the resilience of banks, some studies pointed to the potential negative welfare effects of these policies in terms of wealth and income inequality (Frost and Stralen (2018); Carpantier et al. (2016)). In good times, LTV and DSTI limits may have direct redistributive effects by excluding low income households from the mortgage market. In bad times, macroprudential policy may dampen the increase in inequality by smoothing the credit cycle, thus lowering the probability and the conditional impact of a financial crisis. The relative size of these opposing effects is an empirical question.

To quantify the size of these costs and benefits, we conduct counterfactual simulations comparing wealth and income inequality under four policy scenarios (baseline and adverse scenario, with and without MP) for four euro area countries: Ireland, Italy, Netherlands and Portugal. The analysis combines granular household level data on wealth and income from the Euro Area Household Finance and Consumption Survey (HFCS) together with bank level data from the 2018 Euro Area Stress Test exercise and macroeconomic indicators from the ECB Statistical Data Warehouse.[2] We use the Gini coefficient as a metric for our cost-benefit calculations.

To estimate the benefits of macroprudential measures, we proceed in three steps. First, we use a Bayesian VAR (BVAR) to quantify the macroeconomic impact of a credit crunch conditional on an adverse macroeconomic scenario under different macroprudential policy regimes (i.e. with or without LTV and DSTI limits). In a second step, we match the unemployment and asset price response obtained in the BVAR to household data in order to derive income and wealth distributions under these different policy scenarios. Last, we compute the benefit of the MP measures as the difference in income (wealth) inequality between the adverse scenario without

[1] An LTV limit implies that a loan will be granted only if the borrower's down payment is sufficiently large relative to the value of the house. A DSTI limit excludes borrowers whose monthly mortgage payments exceed a certain portion of their monthly income.

[2] In this paper we also used data from the DNB Household Survey.

borrower-based MP measures and the adverse scenario with these measures in place. The cost is computed in a similar fashion, as the difference in income (wealth) inequality between the baseline scenarios with and without these MP measures in place. The only difference to the benefits calculation is that the macroeconomic response is computed conditional on a loan demand shock at MP measures introduction.

Results show that the imposition of the DSTI and LTV limits results in an increase in the Gini coefficient of wealth ranging from 0.14 percentage points in Italy to 0.58 percentage points in the Netherlands. In the baseline scenario with LTV and DSTI limits in place, two channels affect household wealth. First, the wealth of all households is affected by the impulse response of house, stock and bond prices to the loan demand shock implied by the borrower-based measures. Second, the counterfactual value of wealth of excluded households decreases by the current house value and increases by the initial mortgage amount. The change in wealth inequality is primarily driven by the change in wealth of excluded households after imposition of borrower-based limits. This welfare cost is expected given that *(i)* housing is the main source of wealth for households in the low percentiles of the wealth distribution and *(ii)* borrower-based limits are more binding for the latter households.

Somehow surprisingly, wealth inequality in the adverse scenario with borrower-based measures in place is higher than in the adverse scenario without these limits. While low-wealth households excluded from the mortgage market were shielded from a negative wealth shock following the fall in house prices in the adverse scenario, the decrease in wealth resulting from barriers to house ownership is larger. We derive the unconditional net benefit as the difference between the expected value of the Gini coefficient with and without borrower-based measures, taking into account the change in the crisis probability across policy scenarios. The unconditional benefit of borrower-based measures in terms of wealth inequality ranges from -0.14 percentage points in Italy to -0.58 percentage points in the Netherlands.

Turning to income inequality, a negligible decrease in the Gini coefficient of income is observed after the imposition of LTV and DSTI limits, amounting to less than 0.04 percentage points in the baseline scenario. The small impact on income inequality is due to the fact that two opposing effects affect disposable income following the implementation of borrower-based limits. First, borrower-based limits have a contractionary impact at introduction, resulting in an increase in unemployment. Second, the debt burden decreases and therefore the disposable income of excluded households increases. These two effects cancel each other out, resulting in a muted impact on income inequality in the baseline scenario. In the adverse scenario income inequality remains broadly unchanged. The main reason for this result is the negligible change in the unemployment impulse response in the adverse scenario compared to the counterfactual with borrower-based measures in place. The unconditional benefit of borrower-based measures in terms of income inequality is less than 0.04 percentage points of the Gini coefficient of income.

These results suggest that the welfare costs of macroprudential regulation in terms of wealth inequality are contained, while the benefits in terms of income inequality are negligible.

The remaining part of the paper is organised as follows: section 2 discusses how existing literature informs our analysis, section 3 and 4 present the data and the methodology respectively, section 5 discusses the results and section 6 concludes.

2 Related Literature

The effect of macroprudential policy on inequality must be assessed considering the relation between financial crisis and inequality. If inequality makes a financial crisis more likely to happen, then the welfare implications of central bank policies having distributional effects deserve more attention, as they may increase the crisis probability. If on the other hand a financial crisis results in a rise in inequality, then macroprudential measures may dampen the contractionary effect of the crisis and mitigate the potential rise in inequality.

Based on existing evidence, it remains unclear whether inequality per se can be considered the cause of the crisis or rather its consequence. Results from studies analyzing the direct impact of inequality on the crisis probability find that a rise in income and wealth inequality is a predictor of financial crisis (Kirschenmann et al. (2016), Perugini et al. (2016), Bellettini et al. (2019), Paul (2020), Hauner (2020)). Since excessive credit growth has been identified as a robust predictor of financial crisis (Schularick and Taylor (2012); Mian et al. (2017); Di Maggio and Kermani (2017)), some authors have argued that inequality can lead to a financial crisis by fuelling excessive credit growth. Empirical and theoretical evidence generally confirms that the link between income inequality and debt accumulation is positive (Krueger and Perri (2006); Iacoviello, M. (2008); Kumhof et al. (2015)). In contrast, Bordo and Meissner (2012) find that, while credit booms heighten the probability of a banking crisis, income inequality does not predict credit booms.

Similarly, the sign of the impact of a financial crisis on inequality is ambiguous. Some crisis lead to a persistent increase in inequality (e.g. Asian financial crisis 1998, the post hyperinflation period in CIS countries in 1990s), while other crisis have the opposite effect. The recent global crisis for instance mitigated years of growing inequality in Brazil, since wealthy individuals were more affected by the depreciation of stock exchanges and financial assets (Paiella and Salleo (2019)). Analyzing a panel of OECD countries, Gokmen and Morin (2019) find that inequality does not increase in the aftermath of the financial crisis. In advanced economies inequality tends to decrease after stock market crashes, as wealthy people have higher investments in the stock market. On average, inequality slightly decreases in the first year after the crisis and increases in the years after (Čihák and Sahay (2020)).

Macroprudential policy can break the vicious link between inequality, indebtedness and financial crisis. Several studies document the effectiveness of borrower-based macroprudential measures in curbing credit growth (Bekkum et al. (2019); Ayyagari et al. (2017); Epure et al. (2018)). In one study focusing on the UK mortgage market, the introduction of LTI limits leads to a lower share of high LTI loans, in particular to low-income borrowers, and lowers house price growth in the regions most affected by these measures. These regions experienced lower house price corrections after the Brexit referendum and less mortgages defaults (Peydro et al. (2020)).

The literature on the distributional effects of central bank policies focused mostly on monetary policy. For instance, nonstandard monetary policy seems to have a negligible effect on wealth and income inequality (Lenza and Slacalek (2018)), while contractionary monetary policy shocks have been found to increase income inequality Coibion et al. (2017)). Similarly, the cross-country analysis in Furceri et al. (2018) shows that positive monetary policy shocks increase inequality, in particular in countries with a high share of labor income and lower redistribution.

The distributional impact of macroprudential measures has received less attention. Some studies pointed to the potential negative welfare effects of these policies in terms of wealth and income inequality (Frost and Stralen (2018); Carpantier et al. (2016)). The reasoning is that borrower-based measures such as loan-to-value (LTV) and debt-service-to-income (DSTI) limits may have direct redistributive effects by excluding low income households from the mortgage market. Frost and Stralen (2018) find that countries that use LTV and DSTI limits display higher (gross) income inequality compared to countries that do not use these measures. In the same paper, reserve requirements are associated with a lower income share for the bottom income deciles. A negative association was observed between inequality on the one hand and the leverage ratio and limits on foreign currency lending on the other hand. As pointed by the authors, causality cannot be inferred from these results since country specific factors may determine the choice of a specific macroprudential measure. A related study by Carpantier et al. (2016) calibrates a theoretical model on household level data to explore the determinants of wealth inequality in the presence of LTV limits. The study finds that LTV limits have a positive effect on wealth inequality, while the bequest motive has a negative impact.

In this study, we use a counterfactual simulation to estimate the causal effect of the introduction of borrower based macroprudential measures on wealth and income inequality under a baseline and adverse macroeconomic scenario. We reasoned that, while borrower-based measures may increase wealth inequality at introduction, they may act as a buffer during a financial crisis, mitigating the resulting increase in inequality.

3 Data

The 2014 wave of the euro area Household Finance and Consumption Survey (HFCS) was used. Table 6 shows the HFCS variables used in the simulations. We focus on four countries: Ireland, Italy, Netherlands and Portugal. This heterogeneous group includes countries that recently experienced a real estate crisis (Ireland), a sovereign debt crisis (Portugal, Ireland, Italy) as well as well as a country with a high level of household indebtedness relative to GDP and no recent history of a housing crisis (the Netherlands).[3]

Table 5 in the Appendix shows the summary statistics of wealth and income obtained from the household data in the 4 countries of interest. The number of reporting households ranges from 1,280 in the Netherlands to 8,037 in Italy. The median yearly gross income is significantly higher in Ireland and the Netherlands compared to Italy and Portugal, at €41,472 and €49,095 versus €25,696 and €18,415 respectively. The ranking is similar in terms of total assets, with a median values ranging from €161,986 in Portugal to €268,682 in the Netherlands. Median stock holdings are the highest in Italy at €10,000, followed by median holdings of €3,000, €4,000 and €8,000 in Portugal, Ireland and the Netherlands respectively.

The differences in household indebtedness are significant. The lowest level of outstanding mortgages is reported in Portugal, with a median outstanding mortgage of €90,450 representing around 500% of yearly household income. In Ireland, Italy and the Netherlands median outstanding mortgage amounts are €175,000, €100,000, and €151,000 respectively, representing between 3 and 4 times the yearly household income. The median debt-service-to-income ratio (DSTI) follows a similar pattern, ranging between 12% in Italy and 17% in Portugal.

Table 7 shows the summary statistics of selected variables by income percentile. As expected, the value of the household residence is directly proportional to the household income. With the exception of the Netherlands, the outstanding mortgage follows the same ranking. The LTV and the DSTI decrease smoothly with the increase in income for all countries. The only exception is the LTV for Italy which peaks for households in the 90^{th} percentile of the income distribution.

Considering a typical LTV limit of 80% and a DSTI limit of 30%, table 7 suggests that the LTV limit is by far the most binding constraint for all income percentiles, whereas the DSTI limit is only binding for the 25^{th} and to some extent for the 50^{th} income percentile. Table 7 shows how income and wealth inequality are linked. Low income households are also the ones with the highest levels of indebtedness relative to their income and the assets they own. Therefore these borrowers are the first to be affected by the imposition of borrower based measures, further increasing the concentration of wealth among high-income borrowers.

Table 8 shows the distribution of the employment status by countries. For Ireland, Italy and the Netherlands, the absolute difference between the unemployment rate derived from the HFCS data and the aggregate unemployment rate measured in these countries on December 31, 2014 is between 2 and 3 percentage points (13.33%, 10.71%, 4.24% compared to aggregate rates of 10.91%, 12.72% and 7.15% for Ireland, Italy and the Netherlands respectively). In the case of

[3]Netherlands has the highest level of household-debt-to GDP in the euro area, with values of 110%, 114% and 101% of GDP in the fourth quarter of 2006, 2016 and 2019 respectively.

Portugal, the HFCS unemployment figure of 13.21% comes the closest to the aggregate figure 13.54%.

Quarterly macroeconomic time series for real GDP, inflation, short-term interest rates, long-term nominal yields (LTN), unemployment, loan volumes, loan interest rates, house prices, wages and stock prices for the period ranging from September 1997 to December 2018 were obtained from the ECB Statistical Data Warehouse. Bank level losses in the adverse scenario in the EBA 2018 Stress test were obtained from ECB internal models applied to stress test data submitted by banks.

4 Empirical Approach

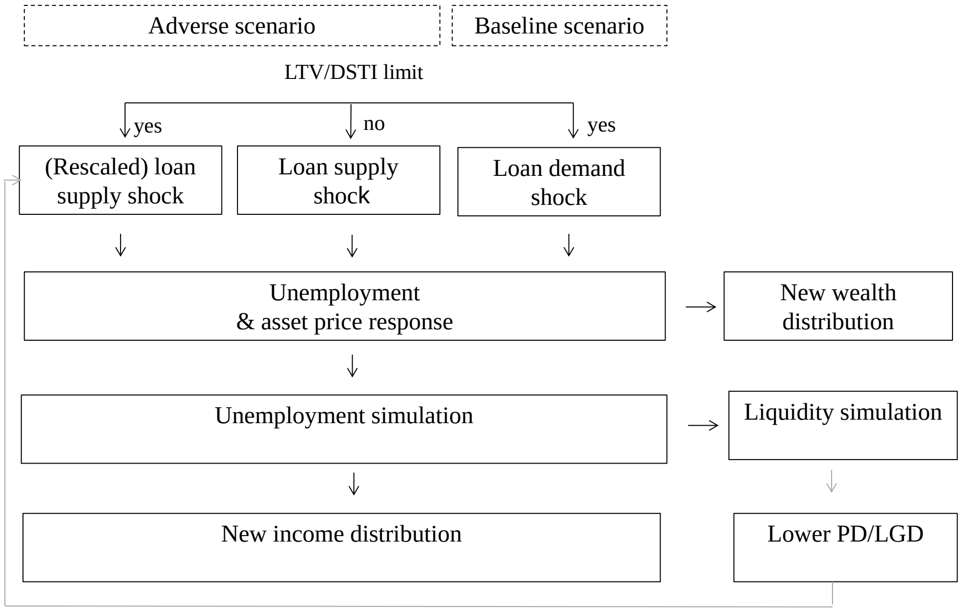
The empirical approach combines the method used by Gross and Poblacion (2017) and Lenza and Slacalek (2018) for matching macro data with the HFCS data, as well as Budnik et al. (2014) for the incorporation of the feedback loop between banks and the macroeconomy following the adverse macroeconomic scenario. The approach includes several modules (see figure 1 below).

Each scenario starts with a loan demand or loan supply shock. In the baseline scenario, we follow the approach of Gross and Poblacion (2017) and assume that the introduction of the borrower-based measures is equivalent to a loan demand shock. The loan demand shock is identified by constraining loan volume to fall together with lending rates in the first quarter of the loan volume shock.

Similar to Budnik et al. (2014), we assume that the adverse macroeconomic scenario is followed by a credit supply shock. Several studies document the importance of credit supply shocks in the aftermath of the Great Financial Crisis, reflecting the emerging consensus according to which banks are an independent source of shocks rather than just passive players transmitting macroeconomic shocks (Nikolay et al. (2012), Fadejeva et al. (2017), Bijsterbosch and Falagiarda (2015)). These studies find that credit supply shocks have been an important driver of business cycle fluctuations in the euro area, with a negative contribution in the aftermath of the financial crisis. The transmission of the credit supply shock to the real economy is also illustrated in studies based on micro-data such as Chodorow-Reich (2014) and Acharya et al. (2018). Chodorow-Reich (2014) find that in the aftermath of Lehman bankruptcy, firms with loans towards banks with a higher exposure to mortgage-backed securities reduced employment by 4 to 5 percentage points more than banks with lower exposure to mortgage-backed securities. Similarly, Acharya et al. (2018) find that firms with loans towards banks with higher sovereign bond exposure during the sovereign debt crisis were less likely to obtain new loans, reducing their investments and employment more than firms with creditors less exposed to sovereign bonds.

For identification, we impose the condition that a decrease in loan volumes is accompanied by an increase in lending rates. To derive the size of the credit supply shock, we assume that banks deleverage by the amount of loan losses incurred in the adverse scenario of the 2018 stress test. In the adverse scenario with borrower-based measures, the credit supply shock will be correspondingly reduced: since borrower-based measures were introduced in the baseline scenario, banks enter the crisis with lower credit risk parameters. The derivation of these new credit risk parameters is described in the liquidity simulation module.

Figure 1. Empirical approach



In a next step, the response of house prices, stock and bond prices to the demand or supply shock in each scenario are matched to the household level wealth data from the household survey to obtain the new wealth distribution. Thereafter the unemployment response to the demand and supply shocks in each scenario is used as input in the employment simulation. The latter simulation is calibrated to the household level employment and demographic data to obtain a new distribution of employment status. The employment status determines the household level income, allowing the derivation of a new income distribution in each scenario.

4.1 Credit demand and supply shocks

We estimate a Bayesian Vector Autoregression (BVAR) to derive structural credit demand (supply) shocks:

$$Y_{i,t} = c_i + \sum_{j=1}^{n} A_i \cdot Y_{i,t-j} + \varepsilon_{i,i} \tag{4.1}$$

Where $Y_{i,t}$ is a vector of 10 macroeconomic variables including real GDP, inflation, short-term interest rates, long-term nominal yields (LTN), unemployment, loan volumes, loan interest rates, house prices, wages and stock prices and p is the number of lag variables. A Minnesota prior is assumed for the residual covariance matrix. Under the Minnesota prior (Litterman, R. (1980), Litterman, R. (1986)), it is assumed that residuals follow a multivariate normal distribution with mean 0 and known variance-covariance matrix, while the endogenous variables present a unit root in their own lags. Sign restrictions are imposed to identify supply and demand shocks borrowing from the identification scheme in Hristov et al. (2011) (see table 9 in the Appendix). We use the BEAR toolbox developed by Dieppe et al. (2016) for estimation.

The loan demand (supply) shocks correspond to the 3 different policy scenarios as shown in table 1 below. The imposition of LTV and DSTI limits is assumed to be equivalent to a credit demand shock equal to the loan volume excluded after the imposition of the limits. We focus on mortgages from the HFCS data set issued in 2006, just before the financial crisis. In turn, the credit supply shock in the adverse scenario is derived from the bank level losses reported in the 2018 stress test adverse scenario aggregated at country level. It is assumed that following the adverse scenario, banks reduce lending by an amount equal to the incurred losses. The scaled supply shock in the adverse scenario with borrower-based measures is obtained by scaling the losses reported by banks in the adverse scenario with the relative change in credit risk parameters induced by LTV and DTSI limits imposition (default probability, PD and loss-given default, LGD) as described in the liquidity simulation module.

Table 1: Overview of scenarios

Macro scenario	Policy scenario	Type of shock
Baseline	LTV/DSTI = No	-
Baseline	LTV/DSTI = Yes	Loan demand
Adverse	LTV/DSTI = No	Loan supply
Adverse	LTV/DSTI = Yes	Loan supply

The response of unemployment and wages to the scenario conditional demand (supply) shocks is used as input in the unemployment simulation to derive a new income distribution. The response of house prices, stock and bond prices is used as input for the derivation of a new wealth distribution in each scenario. The initial income and wealth distribution is obtained from the HFCS data.

4.2 Employment simulation

In this module, the response of macroeconomic variables to the scenario specific demand and supply shock is mapped to the employment distribution of households in the HFCS dataset.

The probability of being employed is a latent unobservable variable (y_i^*), which is assumed to be a function of workers demographics:

$$y_i^* = X_i\beta + \varepsilon_i \tag{4.2}$$

Where ε_i follows a logistic distribution and vector X includes demographic variables for each individual i such as gender, age, education, marital status, a dummy variable taking the value 1 if the host country is the country of birth and 0 otherwise, as well as a constant term. The sample for the regression in equation 4.2 only includes the active population, excluding students, retirees and any other individuals who are unable to work.

Since employment status is observed, while individual employment probability is not, we assume:

$$y_i = \begin{cases} 1 & \text{(employed) if } y_i^* \geq 0 \\ 0 & \text{(unemployed) if } y_i^* \leq 0 \end{cases} \tag{4.3}$$

The regression 4.2 is estimated at country level using the Maximum Likelihood (ML) method. The dependent variable is a binary vector that takes value 1 if the individual i is employed and 0 otherwise. The estimated parameters $\hat{\beta}$ from equation 4.2 are plugged into the logistic function to obtain individual employment probabilities $\hat{p}_i^{emp}$:

$$\hat{p}_i^{emp} = \frac{1}{1 + e^{-X_i\hat{\beta}}} \tag{4.4}$$

The probabilities $\hat{p}_i^{emp}$ are used to simulate employment status by comparing them to random draws ϵ from a uniform distribution in the [0, 1] interval. Following Gross and Poblacion (2017) and Lenza and Slacalek (2018), an individual is employed if $\hat{p}_i^{emp} > \epsilon$. An individual's employment status does not change in the baseline scenario. In all other scenarios, individuals will either remain employed or transition into unemployment, depending on the outcome of the simulation.

The intercept of the logistic regression is adjusted to match the aggregate unemployment rate obtained from the BVAR under each policy scenario. Different from Gross and Poblacion (2017), the intercept varies for low income versus high income individuals, such that the intercept for the low income individuals represents 88% of aggregate unemployment. The differentiation between low income and high income individuals is meant to account for the fact that low income individuals experience higher unemployment than high income individuals, in particular after a recession. The intercepts were calibrated based on data from the Dutch household survey showing that low income individuals account for 88% of the increase in the unemployment in the Netherlands in the 7 years after the 2009 recession.[4] Low income is defined as income lower than the bottom 25 percentile of the country's income distribution.

4.3 Liquidity simulation

This module is used to derive the scaling factor for the credit supply shock in the adverse scenario with borrower-based measures. The scaling factor is derived from the ratio between the average credit losses with and without MP measures in the baseline scenario. Essentially, the scaling is equivalent to a starting point adjustment in the adverse scenario with borrower-based measure in place, since banks enter the adverse scenario with lower PD and LGD parameters. Lower credit losses in the adverse scenario imply a lower need for deleveraging and therefore a lower credit supply shock:

$$cl_{a,MP} = cl_a^{st} \cdot \frac{pd_{MP}^{hh} \cdot lgd_{MP}^{st}}{pd^{hh} \cdot lgd^{st}} \tag{4.5}$$

Where $cl_{a,MP}$ represents credit losses in the adverse scenario with MP measures in place, cl_a the credit losses reported by banks in the EBA 2018 stress test, pd^{hh} is the household default probability computed from the HFCS data conditional on MP measures, pd_{MP}^{hh} is the household default probability as implied by the HFCS data, lgd^{st} the starting point LGD reported by banks in the 2018 stress test and lgd_{MP}^{st} the rescaled starting point LGD that reflects the lower LTV resulting from the imposition of the borrower-based measures.

The default probability pd_s^{hh} of household hh in scenario s is defined as the sum of households that become illiquid in the simulation horizon (12 quarters) over the total number of households. The household will become insolvent if its liquidity inflows are lower than its liquidity outflows. Households' liquidity is simulated under the baseline scenario with and without MP measures in place.

The following 4 inputs are required for the liquidity simulation: *(i)* the employment simulation results from section 4.2, aggregated at household level, *(ii)* an unemployment benefit vector for the entire sample of active population and *(iii)* an employment income vector for the entire sample of active population and *(iv)* the change in the value of liquid assets, where liquid assets are defined as the sum of cash, bonds and stocks holdings.

Since default probabilities are estimated from the bank's perspective, we do no allow for any role of liquid assets to smooth consumption. Creditors will only have recourse to assets pledged as collateral in case of borrower default. Given that the liquidation of collateral is a lengthy and costly procedure, banks typically only consider income and not assets for the assessment of borrower creditworthiness in a loan application.

[4] The ratio has a value of 80% in 2009 and reaches 87% in 2015.

The unemployment benefit transfers and employment wages are obtained from the HFCS survey data. The salaries of individuals' transitioning to unemployment under each scenario are replaced with their estimated unemployment benefits. These benefits are assumed to be a function of workers past employment salaries. Given that each country has their own national unemployment scheme, the transfers are calculated replicating each country's methodology.[5] Missing employment income observations are imputed using predicted values from a regression having the HFCS reported annual employment salary as a dependent variable and demographic variables including gender, age, education, marital status and a dummy variable indicating whether the host country is the country of birth as predictors.

Once all three inputs are defined, labor income is computed as follows:

$$inc^{l}_{s,i} = emp_{s,i} \cdot inc^{emp}_{i} \cdot (1 + \gamma^{wage}_{s}) + (1 - emp_{s,i}) \cdot transf^{unemp}_{i} \tag{4.6}$$

Where $emp_{s,i}$ is the employment indicator for individual i in scenario s obtained in section 4.2 and takes the value 1 if the individual is employed and 0 otherwise, γ^{wage}_{s} is the scenario-specific 12-quarter impulse response of wages and inc^{emp}_{i} and $transf^{unemp}_{i}$ are the individual employment salary and unemployment benefit, respectively, as described above.

Thereafter, results are aggregated at the household level by pooling together all the individuals who belong to the same household. In addition to labor income, total household level income is computed considering any other income sources households report in the HFCS Survey:

$$inc^{tot}_{s,hh} = inc^{l}_{s,hh} + inc^{oth}_{s,hh} \tag{4.7}$$

Where $inc^{oth}_{s,hh}$ represents any other sources of income (pension, real estate property income, social transfers other than unemployment or regular private transfers).

The next step in the liquidity simulation, is to calculate the 12-quarter-change of the market value of households' stocks and bond holdings:

$$\Delta b_{hh,s} = b_{hh} \cdot \gamma^{b}_{s} \quad \text{and} \quad \Delta s_{hh,s} = s_{hh} \cdot \gamma^{s}_{s} \tag{4.8}$$

Where b_{hh} indicates bond holdings, γ^{b}_{s} is the scenario-specific 12-quarter-impulse response on bond yields, s_{hh} represents stock holdings, γ^{s}_{s} is the scenario-specific 12-quarter-impulse response on stock prices.

[5]An overview of OECD countries' National Unemployment Schemes can be accessed under the following link: `http://www.oecd.org/social/benefits-and-wages`.The transfers are computed following each country's methodology as they stand as of August 2020.

The household level liquidity status is computed as the difference between household's total income and total expenditures. Expenditures include debt repayments such as mortgage payments for households with outstanding mortgages, house rental payments and expenses for consumption of goods and services:

$$\Delta liq_{s,hh} = inc^{tot}_{s,hh} + \Delta b_{hh,s} + \Delta s_{hh,s} - (1 - I^{excl}_{hh,s}) \cdot min(d^{out}_{hh}, d^{rep}_{hh}) - exp^{cons}_{hh} \tag{4.9}$$

Where I^{excl}_s represents a binary vector taking the value 1 if the household had a mortgage outstanding that did not satisfy the new LTV and DSTI limit under scenario s and 0 otherwise, d^{rep}_{hh} indicates the monthly debt payment, d^{out}_{hh} indicates total outstanding debt and exp^{cons}_{hh} represents households' monthly consumption on goods and services.[6] All variables are adjusted to monthly values.

If the liquidity of a household becomes negative as a result of the macro-financial conditions of each scenario, the individual is unable to meet its outstanding debt payment obligations and is therefore considered to be in default. The default probability PD is defined as the sum of the number of defaulting households relative to the total number of households in the country N_c.[7]

$$PD^{hh}_{c,s} = \frac{1}{N_c} \Sigma^{N_c}_{hh=1} \mathbb{1}_{\Delta liq_{s,hh}<0} \tag{4.10}$$

The LGD is estimated using a structural model having the LTV ratio and the cure rate as main input variables (see Dees S. et al (2017) for details):

$$LGD = (1 - Cure) \cdot \frac{LTV - SR}{LTV} + AdmCosts \tag{4.11}$$

where $Cure$ represents the cure rate, LTV the loan-to-value ratio. The sales ratio SR captures the discount upon collateral liquidation. $AdmCosts$ represent administrative costs upon liquidation and are calibrated at 5%. The sales ratio is assumed to be normally distributed with mean μ and standard deviation σ. Assuming that the recovery rate is equal to the product between the collateral value and the sales ratio and using the definition of the loan-to-value ratio, the sales ratio can be computed as:

$$SR = \mu \left[\phi \left(\frac{LTV - \mu}{\sigma} \right) - \phi \left(\frac{-\mu}{\sigma} \right) \right] + \frac{\sigma}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2\sigma^2}} + LTV \left[1 - \phi \left(\frac{LTV - \mu}{\sigma} \right) \right] \tag{4.12}$$

After plugging in expression for the sales ratio in equation 4.11, the LGD is computed using starting point values of the LTV and cure rates reported by banks in the 2018 stress test. The

[6]Consumption values are obtained from the HFCS.

[7]The survey weights included in the HFCS are used to compute the total number of households with mortgages outstanding in country c.

relative change in the LGD is computed by adjusting the LTV reported by banks with the relative change in the average country LTV obtained from the HFCS data after imposition of the LTV limit.

All calculations are initially run using a grid for the LTV limit ranging from 50% to 90% and a DSTI limit ranging from 30% to 50%. Given that final results do not change materially for different DSTI values, cost benefit calculations are performed with a constant DSTI limit at 30% and a LTV limit at 80%.

Finally, the relative change in the product of the aggregate PD and LGD in the baseline scenario with and without MP measures is used for the scaling of the credit supply shock in the adverse scenario in equation 4.5.

4.4 Net benefit of borrower-based measures

In the last step, the wealth and income distributions derived in each scenario are used to compute income and wealth inequality. Inequality is assessed using the Gini coefficient. Alternative measures of inequality, such as the ratio between the 75^{th} and the 25^{th} percentile of the income and wealth distribution are used. The results remain qualitatively unchanged.

The benefit of borrower based measures in terms of wealth inequality is computed as the difference between the Gini coefficient in the adverse scenario without and with borrower-based measures in place:

$$b^{w,MP} = gini_a^w - gini_a^{w,MP} \tag{4.13}$$

Similarly, the cost of borrower based measures is computed as the difference between the Gini coefficient in the baseline with and without borrower-based measures in place:

$$c^{w,MP} = gini_{w,MP}^w - gini_b^w \tag{4.14}$$

Where $gini_a^{w,MP}$ and $gini_a^w$ refer to the wealth-based Gini coefficients with and without borrower-based measures in place in the adverse scenario respectively, while $gini_b^{w,MP}$ and $gini_b^w$ refer to the wealth-based Gini coefficients with and without borrower-based measures in place in the baseline scenario. The calculations are performed analogous for the costs and benefits with respect to income inequality.

The calculations above estimate the benefit conditional on a crisis. The unconditional benefit is computed as the difference between the expected values of the Gini coefficient with and without borrower-based measures, taking into account the change in the crisis probability across policy scenarios:

$$\hat{b}^{w,MP} = \left(p \cdot gini_a^w + (1-p\cdot)\, gini_b^w\right) \quad - \left(p_{MP} \cdot gini_{a,MP}^w + (1-p_{MP}) \cdot gini_{b,MP}^w\right) \tag{4.15}$$

Where p_{MP} and p refer to the crisis probability with and without borrower-based measures in place respectively. The first bracket shows the expected Gini coefficient of wealth without borrower-based measures in place. The second bracket shows the expected Gini coefficient of wealth with borrower-based measures in place.

Similarly, the unconditional benefit in terms of income inequality is computed as:

$$\hat{b}^{i,MP} = \left(p \cdot gini_a^i + (1-p\cdot)\, gini_b^i\right) - \left(p_{MP} \cdot gini_{a,MP}^i + (1-p_{MP}) \cdot gini_{b,MP}^i\right) \tag{4.16}$$

The crisis probability is computed as the fitted value from the model by Schularick and Taylor (2012). The crisis probability in their model is a function of the log changes in the credit-to-GDP ratio. The model is estimated for 14 advanced economies over the period 1870–2008. Since credit growth and the crisis probability are negatively correlated, the loan demand shock after imposition of LTV and DSTI measures in the baseline scenario will lead to a reduction in the crisis probability, changing the expected gini coefficient.[8]

5 Results and Discussion

5.1 Credit demand and supply shocks

Figures 9 and 10 in the Appendix report the cumulative impulse responses conditional on a one standard deviation loan demand and supply shock respectively.

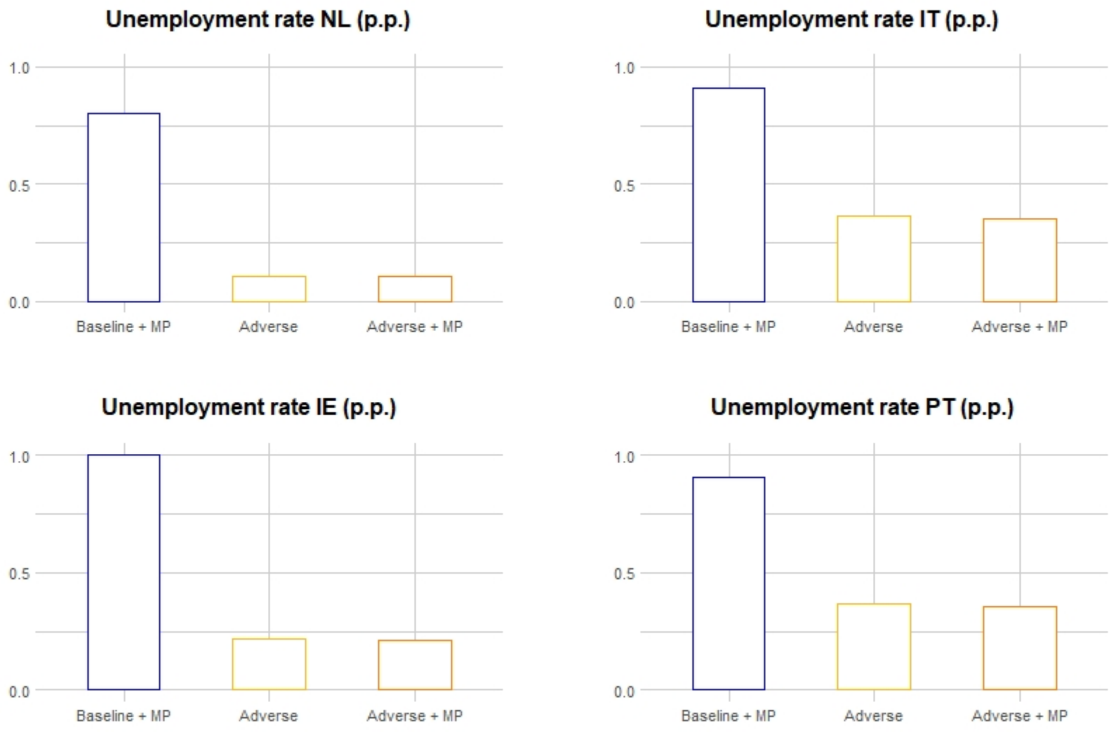
The impulse responses in each scenario are scaled with the scenario specific change in loan volume, expressed in loan growth standard deviations. In the case of the loan demand shock, an LTV limit of 80% in combination with a DSTI limit of 30% implies a decrease in loan volume of 7.6% for Ireland, 5.36% for Italy, 4.46% for Portugal and 5.05% for the Netherlands.[9] Expressed in standard deviations of loan growth, the latter change in loan volume corresponds to 1.7 standard deviations in Ireland, 2.5 in Italy, 4.9 in Portugal and 2.3 in the Netherlands.

In turn, the magnitude of the loan supply shock is given by the amount of credit losses incurred by banks in the adverse scenario in the 2018 stress test. These credit losses are equivalent to a

[8]To estimate fitted values of the crisis probability, we used specification number (9) in table 4 as it performed better than the specifications using credit growth as predictors.

[9]The change in loan volume implied by the combination of the 80% LTV and 30% DSTI limit is only applied to the share of loans represented by mortgages. The mortgage share ranges from 0.55 in Portugal to 0.65 in the Netherlands.

Figure 2. Impulse Responses. Unemployment rate



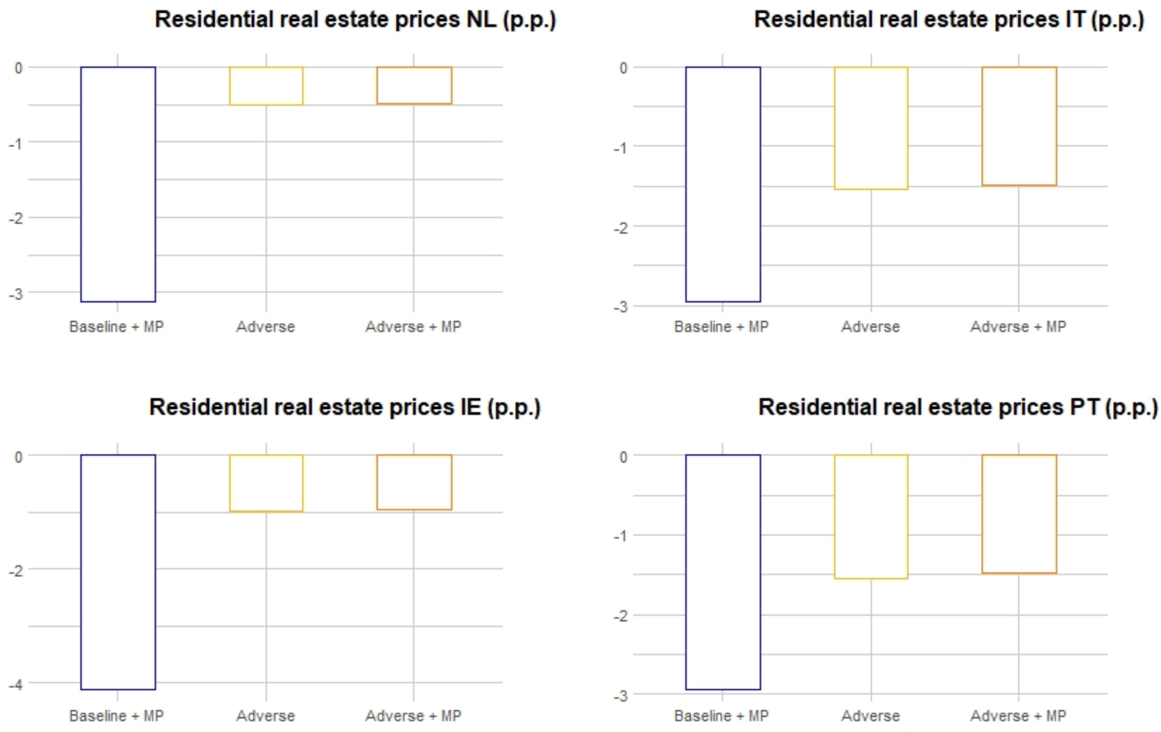
Note: The chart shows the scaled impulse responses of unemployment for the different scenarios. The impulse response calculation from the BVAR is described in section 4.1.

decrease in loan volume, ranging from 0.85% in the Netherlands to 2.34% in Italy. Expressed in standard deviations, the decrease in loan volume ranges from 0.4 standard deviation in the Netherlands to 1.5 in Portugal. In the adverse scenario with borrower-based measures in place, mortgage credit losses are scaled down with a factor computed as in equation 4.5, reflecting the lower credit risk parameters implied by the borrower-based measures. The scaling factor ranges from 0.5 in Italy to 0.9 in Ireland and is applied to the share of mortgage losses out of total credit losses in the adverse scenario.The share ranges from 0.1 in Italy to 0.3 in Ireland.

Figures 2, 3, 4 in this section and figure 11 in the Appendix report the scaled impulse responses by scenario for each of the main 4 variables of interest: unemployment, house prices, stock prices and long-term nominal yields. After imposition of borrower-based measures in the baseline scenario, the unemployment response ranges from 0.8 percentage points in the Netherlands to 1 percentage point in Ireland. In contrast, the unemployment response after the adverse scenario loan supply shock is considerably lower, ranging between 0.1 percentage points in the Netherlands to 0.4 in Portugal and Italy.

The material difference between the unemployment response in the two scenarios above is the significantly higher contraction in credit in the baseline scenario with borrower-based measures in place compared to the adverse scenario. The largest gap can be observed in Ireland, with a

Figure 3. Impulse Responses. Residential real estate prices



Note: The chart shows the scaled impulse responses of house prices rates for the different scenarios. The impulse response calculation from the BVAR is described in section 4.1.

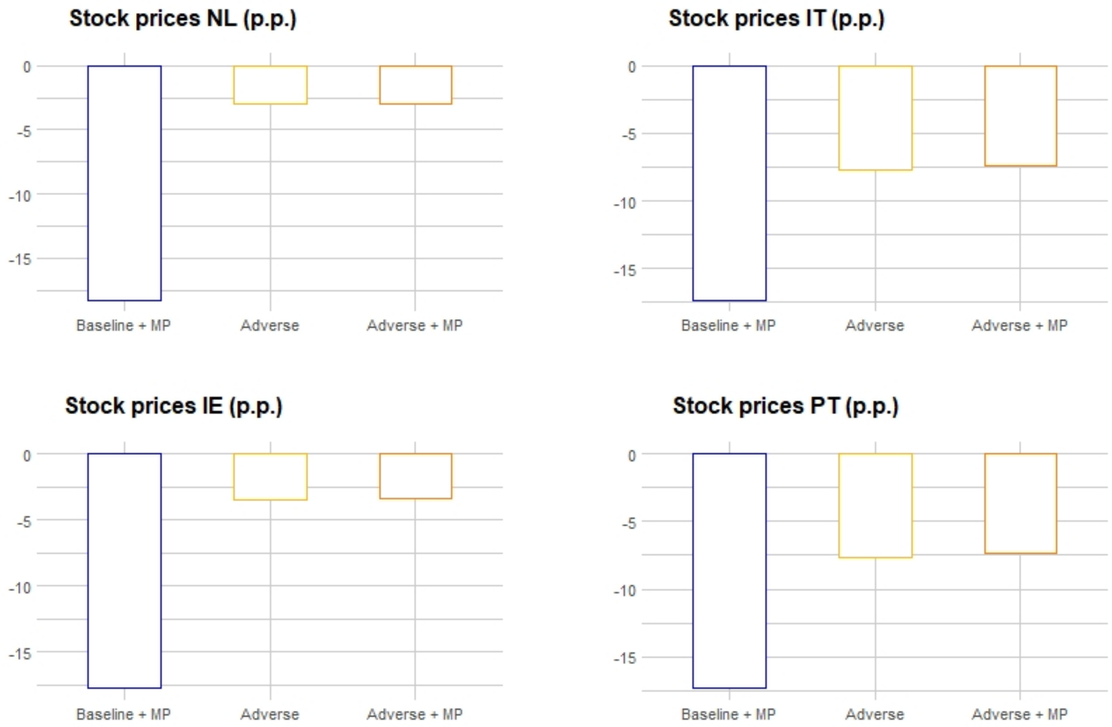
7% loan contraction in the baseline with macroprudential measures versus 1.6% in the adverse scenario. The supply shock driven contraction of credit in the adverse scenario is comparable with the estimates by Nikolay et al. (2012), yet significantly lower than estimates of Bijsterbosch and Falagiarda (2015) during the crisis period. Due to the low weight of the mortgage credit losses in combination with the moderate response of risk parameters,[10] the unemployment response for the adverse scenarios with and without borrower-based measures in place is almost identical. The unemployment response across scenarios is the main driver for the changes in income inequality reported in section 5.4.

The same pattern discussed for the unemployment response can be observed for the house prices. The impulse response of house prices to a one standard deviation loan demand shock ranges from -2.3 percentage points in Ireland to -1.1 percentage points in Italy (figure 9 in the Appendix). After imposition of borrower-based limits in the baseline scenario, the house price correction ranges from -2.9 percentage points in Portugal to -4.1 percentage points in Ireland (figure 3). Following the credit supply shock in the adverse scenario, the drop in house price is significantly lower, with values between -0.5 percentage points in the Netherlands to -1.5 percentage points

[10]See figures 7 in the next section and figure 12 in the Appendix for a comparison of the change in risk parameters after introduction of the LTV and DSTI limits across countries.

in Portugal (3). As expected, the figures for the adverse scenario with borrower-based measures in place are almost identical to the adverse scenario estimates.

Figure 4. Impulse Responses. Stock prices



Note: The chart shows the scaled impulse responses of unemployment for the different scenarios. The impulse response calculation from the BVAR is described in section 4.1.

The stock price decrease following the MP limits implied loan demand shock amounts to around -18 percentage points in Ireland and the Netherlands and around -17 percentage points in Italy and Portugal. In the adverse scenario, the house price drop is less severe, at around -3 percentage points in Ireland and the Netherlands and -7 percentage points in Italy and Portugal. Last, the response of the long term nominal (LTN) rates to the MP limits implied loan demand shock amounts to -0.1 percentage points. The loan supply shock in the adverse scenario results in a LTN drop 0.4 of percentage points in Italy and Portugal and an increase of 0.03 percentage points in Ireland. The response in the adverse scenario with MP limits is almost identical.

The rescaled impulse responses are added to the level of the macroeconomic variable specified by the EBA scenario. The resulting set of macroeconomic variables account for the feedback between the banking sector and the macro economy following the adverse scenario. The unemployment response is a key input for the employment and the liquidity simulation, ultimately determining the income distribution in each scenario. The asset price changes are used as input to determine the new wealth distribution in each scenario.

5.2 Employment simulation

The results of the logistic regression from equation 4.2 are reported in table 2.

Table 2: Employment probability

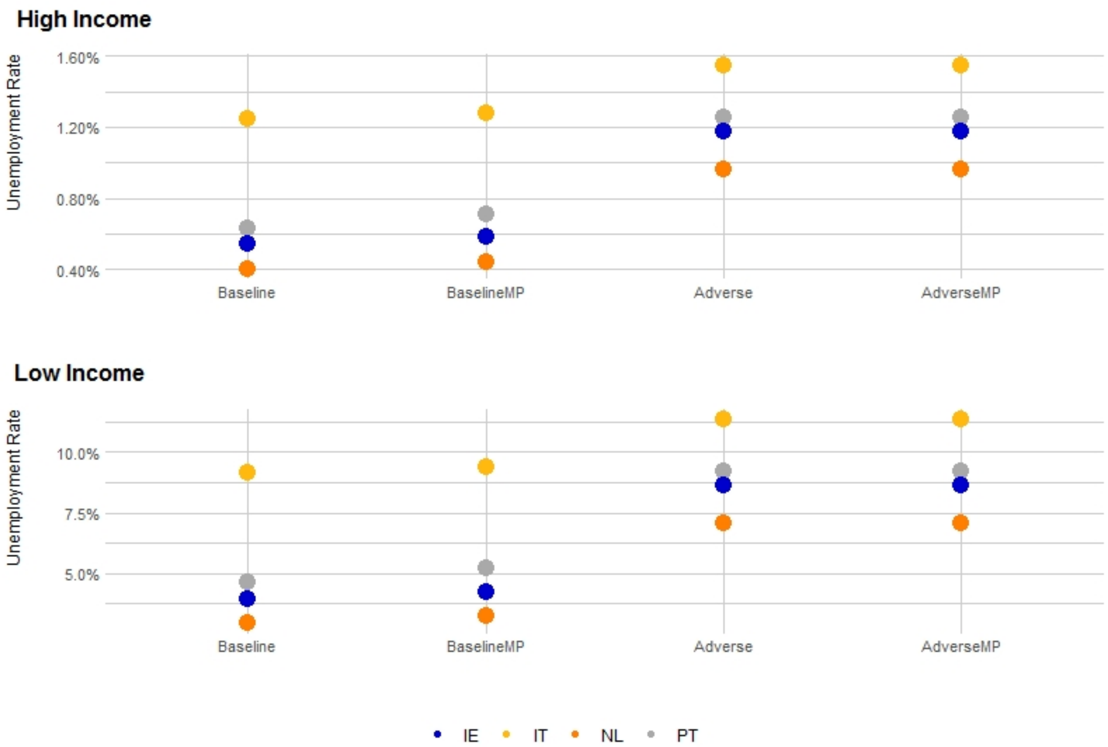
Variable	IE	IT	NL	PT
Intercept	0.37***	-1.39***	2.92***	-0.02
	(0.08)	(0.14)	(0.53)	(0.14)
Age	-	0.05***	-0.02*	0.01***
		(0.00)	(0.01)	(0.00)
Male	-0.10	0.08	-0.23	0.10
	(0.06)	(0.06)	(0.24)	(0.06)
Marital status	0.99*	0.74*	0.65	0.75*
	(0.06)	(0.07)	(0.25)	(0.06)
Education	1.21*	0.78*	0.18	1.11*
	(0.07)	(0.09)	(0.24)	(0.08)
Country birth	0.31*	0.00*	0.28	0.14*
	(0.08)	(0.09)	(0.3)	(0.09)

Note: This table reports the results of the logistic regression having the employment status as a dependent variable and age, education, gender as covariates. Country birth is a dummy variable indicating taking the value 1 if the host country is the country of birth and 0 otherwise.

Married and individual with a high level of education are more likely to be employed. Similarly, being born in the host country increases the probability of being employed. The coefficients of these variables are positive and weakly significant in all countries except the Netherlands. Men are more likely to be employed in Italy and Portugal and more likely to be unemployed in Ireland and the Netherlands, but the effect is not statistically significant. Finally, older people are more likely to be employed in Italy and Portugal, while in the Netherlands the opposite is the case. No data on age was available for Irish respondents.

The results of the unemployment simulation are shown in figure 5, separately for low income and high income individuals. The scenarios with borrower-based measures assume an LTV limit of 80% and a DSTI limit of 30%. Results remain qualitatively unchanged for different combinations of the LTV/DSTI limits. In the case of low income individuals, the imposition of borrower based measures in the baseline scenario leads to an increase in unemployment ranging between 0.3 percentage points in Ireland to 0.6 percentage points in Portugal. In the adverse scenario with LTV/DSTI limits in place, the decrease in unemployment compared to the adverse scenario without DSTI/LTV limits ranges between 0.02 in Ireland and 0.2 percentage points in Portugal (lower panel). For high income individuals, the impact is negligible, the increase in the baseline ranges between 0.03 in Italy and 0.08 percentage points in Portugal, while in the adverse scenario the impact is close to 0 in 3 out of 4 countries (upper panel).

Figure 5. Impact of DSTI/LTV limits on unemployment



Note: The upper panel shows the results of the unemployment simulation for high income individuals across policy scenarios. The lower panel shows the results of the unemployment simulation for low income individuals. Low income individuals are those with an income lower than the 25^th percentile of the country distribution. The scenario with borrower-based measures in place ('MP') assumes an LTV limit of 80% and a DSTI limit of 30%.

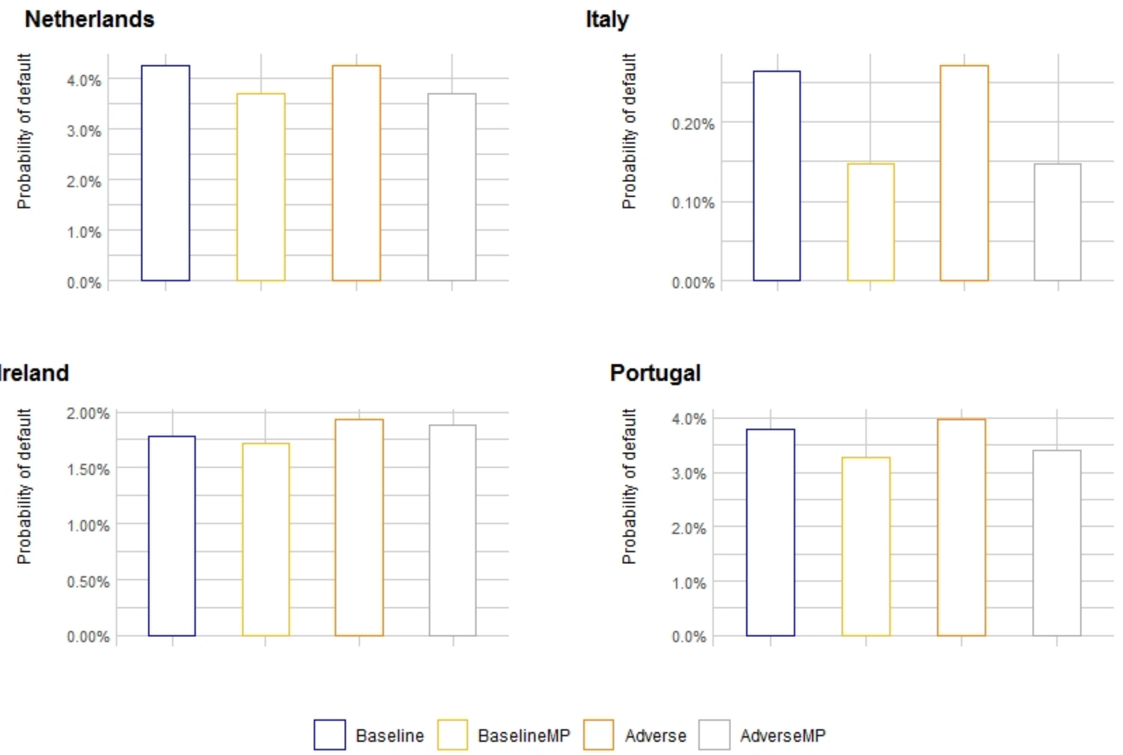
5.3 Liquidity simulation

Figure 6 shows the default probability (PD) with and without borrower-based measures assuming a DSTI limit of 30% and an LTV limit of 80% in the adverse and baseline scenario.[11] Figure 12 in the Appendix shows the PD for different DSTI limits.

The impact of macroprudential measures on the default probability is ambiguous. Since a lower debt burden eases household budget constraints, exclusion from the mortgage market is expected to decrease the default probability. On the other hand, since the loan demand shock implied by the LTV/DSTI measures has a small contractionary effect, as shown by the increase in unemployment in figure 10, default probability may increase after the introduction of borrower-based measures. The counter-intuitive decrease in the PD as the DSTI limit is relaxed in the case of Ireland illustrates this trade-off (see figure 12).

[11]The low PD in Italy is driven by the relative high weight of bond holdings relative to other countries and the high long term nominal yield of Italy in the baseline scenario, with a value of 4.2 p.p. versus 1.1, 1.7 and 3 p.p. in the Netherlands, Ireland and Portugal respectively. The high weight of bond holdings combined with a high sovereign bond yield for Italy results in a PD of 0.26% in the baseline scenario compared to 1.78% for Ireland and 3.78% for Portugal.

Figure 6. Impact of macroprudential policy regimes on PDs

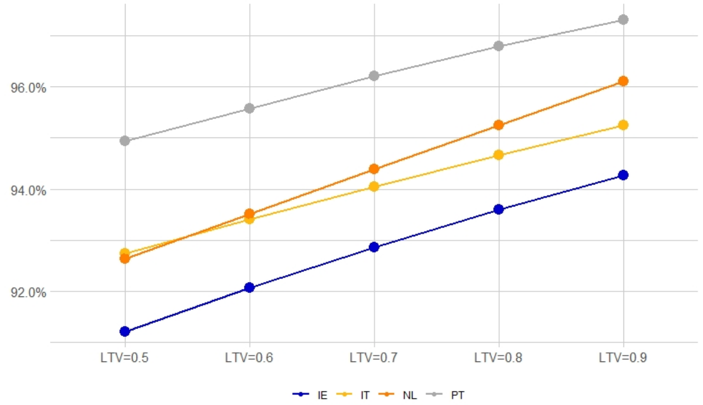


Note: The chart shows the PD before and after the imposition of a DSTI limit of 30% and LTV limit of 80% under both macroeconomic scenarios. The PD is obtained from the liquidity simulation in section 4.3.

The PD and LGD estimates above are used to derive a scaling factor for the credit supply shock in the adverse scenario with borrower-based measures in place. The scaling factor was determined as the product of the ratios of PD and LGD with and without borrower-based measures in place assuming an LTV limit of 80% and a DTSI limit of 30%. The factor has a value of 0.5 for Italy, around 0.85 for Ireland and Portugal and 0.9 for the Netherlands.

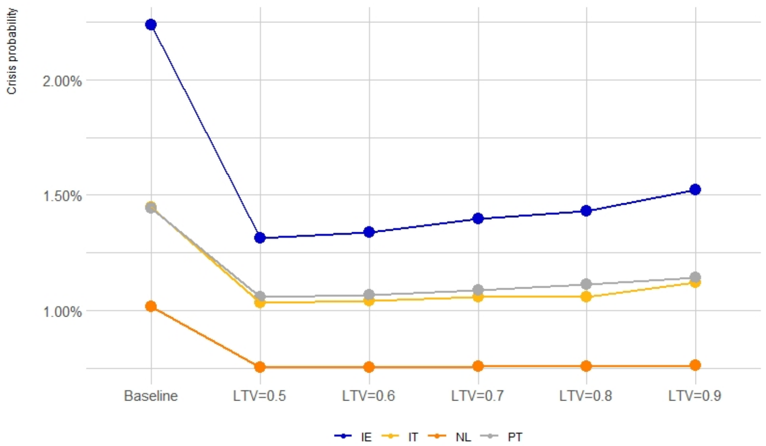
Figure 7 shows the ratio between the LGD with and without borrower-based measures in place for an DSTI limit of 30% and an LTV limit ranging between 50% and 90%. Note that only mortgages issued in 2006 were considered, which considerably reduces the scope of eligible mortgages for this analysis. As expected, both the PD and the LGD decrease after the LTV/DSTI limits are imposed. The LGD increases monotonously as the LTV limit is relaxed, while the PD increases in the DSTI limit (see figures 7 and 12). These results are consistent with the findings from Gross and Poblacion (2017) indicating that the DSTI limits have a stronger negative impact on the PD while the LTV limit leads to a higher reduction in the LGD.

Figure 7. Impact of LTV limits on LGDs



Note: The chart shows the ratio between the LGD after the imposition of the DSTI and LTV limit using as input (i) the starting point LGDs reported by banks in the 2018 stress test and (ii) the relative decrease in the average country LTV after imposition of the LTV limits as implied by the HFCS data.

Figure 8. Crisis probability



Note: The figure shows the crisis probability conditional on the introduction on the borrower-based measures. The crisis probability is computed as indicated in section 4.4. using the model by Schularick and Taylor (2012). A DSTI limit of 30% was assumed.

Turning to the crisis probability conditional on the introduction of borrower-based measures, chart 8 shows that the crisis probability experiences a significant drop across the values of the LTV limits considered. The baseline crisis probability ranges from 1.01% in the Netherlands to 2.24% in Ireland. After the imposition of the DSTI/LTV limits, the absolute drop in the crisis probability ranges from 0.26 percentage points in the Netherlands to 0.9 percentage points in Ireland. These probabilities will be used in the next section for the cost-benefit calculations.

5.4 Costs and benefits of borrower-based measures

Turning to the main question of this study, this section analyzes the distributional consequences of the imposition of DSTI and LTV limits under different macroeconomic scenarios. The results presented in this section refer to a cap of 80% and a DSTI limit of 30% for mortgages issued in 2006.

Tables 11 in the Appendix shows the wealth distribution and the relative change in wealth after LTV and DSTI limits imposition in the baseline scenario. With the exception of Italy, exclusion from the mortgage market has a lower relative impact on high-wealth households (75^{th} and 90^{th} percentile) compared to low-wealth households (25^{th} and 50^{th} percentile). In Italy, households in the 90^{th} percentile see their wealth decrease by 2.5%, compared to only 1.1% for households in the 25^{th} percentile of the wealth distribution. For all countries except Portugal, the wealth impact peaks for households in the 50^{th} percentile, with a decrease in wealth ranging from -2.8% in Italy to -6.9% in the Netherlands. In Portugal, the largest wealth impact of the imposition of borrower-based measures is for households in the 25^{th} percentile, with a decrease in wealth of -12.4%.

Two channels affect household wealth in the baseline scenario with LTV and DSTI limits. First, the wealth of all households is affected by the impulse response of house, stock and bond prices to the loan demand shock implied by the borrower-based measures. Second, the wealth of excluded households decreases by the current house value and increases by the initial mortgage amount. The change in wealth inequality is primarily driven by the change in wealth of excluded households after imposition of borrower-based limits. This is because housing represents a larger share of wealth for households in the lower compared to households in the upper percentiles of the wealth distribution. The former households are also more likely to be affected by the imposition of borrower-based limits (table 7 in the Appendix).

Table 3 reports the Gini coefficient of wealth across the four combinations of macroeconomic and policy scenarios. In the baseline scenario, the imposition of the DSTI and LTV limits results in an increase in the Gini coefficient ranging from 0.14 percentage points in Italy to 0.58 percentage points in the Netherlands. This difference is carried over in the adverse scenario, with wealth inequality with borrower-based measures in place between 0.03 and 0.43 percentage points higher than in the counterfactual adverse scenario without these measures.

Wealth inequality in the adverse scenario with borrower-based measures in place is higher than in the adverse scenario without these limits. Low-wealth households that were excluded from the mortgage market in the counterfactual baseline scenario were shielded from a negative wealth shock due to the drop in house prices in the adverse scenario. Nevertheless, the decrease in wealth resulting from not owning a house in the first place is larger. The unconditional net benefit is computed as the difference between the expected value of the Gini coefficient with and without borrower-based measures, taking into account the change in the crisis probability across policy scenarios, as in equation 4.15 (see column (7) in table 3). The unconditional benefit is negative in all countries, ranging from -0.14 percentage points in Italy to -0.58 percentage points in the Netherlands. After considering the decrease in the crisis probability following the imposition of borrower-based measures, the positive impact on wealth inequality resulting from LTV and DTSI limits imposition in the baseline scenario dominates the negative effect on inequality resulting from lower house price shocks in the adverse scenario.

Table 3: Net wealth inequality across scenarios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline MP=no	Baseline MP=yes	Cost (2)-(1)	Adverse MP=no	Adverse MP=yes	Benefit (4)-(5)	Net benefit (uncond.)
IE	67.14%	67.69%	0.54%	67.17%	67.41%	-0.24%	-0.54%
IT	58.74%	58.88%	0.14%	58.80%	58.82%	-0.03%	-0.14%
NL	56.54%	57.12%	0.58%	56.59%	57.02%	-0.43%	-0.58%
PT	65.28%	65.68%	0.40%	65.47%	65.54%	-0.09%	-0.40%

Note: The table reports the Gini coefficient of net wealth across the 4 combinations of macroeconomic and macroprudential policy scenarios. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

Table 12 in the Appendix shows total income distribution and the relative change in income after LTV and DSTI limits imposition in the baseline scenario. The magnitude of the income decrease is significantly lower compared to the decrease in wealth. The reason for the muted impact of the borrower-based measures on income is that two opposing effects are at play. The decrease in debt burden of excluded households increases available income, while the increase in unemployment resulting from the loan demand shock tends to decrease available income. The two effects cancel each other out, resulting in a marginal change in income. For the most affected income segment, the 50^{th} percentile, the impact ranges between -0.33 percentage points in Portugal to -0.53 percentage points in the Netherlands. The only exception is Ireland for which the strongest impact is observed for households situated in the 75^{th} and 90^{th} percentile of the income distribution.

Table 4 reports the Gini coefficient of income across the four combinations of macroeconomic and policy scenarios. In the baseline scenario, a negligible decrease in the Gini coefficient is observed after LTV and DSTI limits imposition, amounting to less than 0.04 percentage points.

As discussed above, the negative impact of unemployment on disposable income is compensated by the reduction in the debt burden of low income households, resulting in a muted impact on income inequality in the baseline scenario. No difference is observed in terms of income inequality in the adverse scenario conditional on the introduction of the LTV and DSTI limits (see columns (4) and (5) in table 4 and the left panel of figure 13). The unconditional benefit of borrower-based measures is marginally positive, ranging from 0.04 percentage points for Italy to 0.16 percentage points for Ireland (column (7) in table 4).

Table 4: Income inequality across scenarios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline	Baseline	Cost	Adverse	Adverse	Benefit	Net benefit
	MP=no	MP=yes	(2)-(1)	MP=no	MP=yes	(4)-(5)	(uncond.)
IE	37.16%	36.99%	-0.16%	37.33%	37.33%	0.00%	0.16%
IT	40.58%	40.54%	-0.04%	40.56%	40.56%	0.00%	0.04%
NL	34.01%	33.97%	-0.04%	34.01%	34.01%	0.00%	0.04%
PT	42.32%	42.20%	-0.12%	42.29%	42.28%	0.00%	0.12%

Note: The table reports the Gini coefficient of income across the 4 combinations of macroeconomic and macroprudential policy scenarios. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

As discussed in section 5.1, the reason for the stable income inequality in the adverse scenario is the negligible change in the unemployment response in the adverse scenario compared to the counterfactual with borrower-based measures in place. The driver for this result is the low weight of mortgage credit losses in banks' total impairments in combination with the moderate response of credit risk parameters.

5.5 Robustness Checks

5.5.1 Linear projections

As a robustness check, the loan demand shocks for house prices, stock prices and wages are estimated via linear projections (Jordá, O. (2005)), similar to the approach taken in Lenza and Slacalek (2018). To this end, the BVAR is estimated on a restricted set of variables (GDP growth, CPI, unemployment, loan growth, short-term interest rates, lending rates and long-term nominal yields). The resulting structural shocks are used as inputs to compute the impulse response of the remaining variables (house prices, stock prices and wages). To estimate the impulse response to the loan demand or supply shock of variable x at horizon h, we estimate a regression of the form:

$$x_{t+h} = \alpha + \beta u_t + \gamma(L)x_t + \varepsilon \tag{5.1}$$

where u_t represents the structural shocks obtained from the BVAR, (L) the lag operator (up to the third lag in our calculations) for the variable of interest x. The regression is estimated using the Bayesian technique with Minnesota priors. Tables 13 and 14 in the Appendix report the Gini coefficients of wealth and income respectively resulting from the alternative approach for deriving the impulse response to the loan demand and supply shocks. Results remain qualitatively unchanged. The increase in wealth inequality after the introduction of borrower-based measures in the baseline scenario ranges between 0.06 percentage points in Italy to 0.52 percentage points in the Netherlands. The latter increase in wealth inequality is carried over in the adverse scenario. The unconditional benefit in terms of wealth inequality is negative. Similarly, the unconditional benefit in terms of income inequality remains almost unchanged at about 0.05 percentage points in Portugal and Ireland and -0.02 percentage points in Italy and the Netherlands.

5.5.2 Consumption expenditures

Consumption expenditures in survey data are known to be affected by measurement error. This is often due to the survey design: households are asked to report their monthly consumption expenditure in one question. Gray et al. (2008) and D'Ardenne and Blake (2012) analysed this phenomenon and concluded that survey data usually tends to underestimate actual consumption. To control for this, Browning et al. (2014) propose to recalculate consumption values sourcing data from the same survey by subtracting savings (or change in wealth) from gross income.

Since monthly saving figures are not available in the HFCS, we repeated the simulations described in section 4.3 using Eurostat data. We used country-level data on final consumption expenditure of households. We matched the HFCS definition of consumption[12] to aggregate Eurostat data by adding together the most relevant consumption categories from the Eurostat breakdown.[13] In a last step, the consumption by household in each country is scaled by the ratio between the household and the average country consumption ratio in a given country reported in the HFCS.[14]

Chart 15 in the Appendix shows that the consumption estimates derived from Eurostat' tend to be larger than the ones reported in the HFCS.

Charts 16 and 17 in the Appendix show the PD in the baseline scenario under varying LTV and DSTI limits. Since consumption expenditures are higher for all countries, the estimated default

[12]HFCS consumption refers to "all household expenses including food, utilities, etc. but excluding consumer durables (e.g. cars, household appliances), rent, loan repayments, insurance policies, renovation, etc."

[13]Considered categories are: Food and non-alcoholic beverages, alcoholic beverages, tobacco and narcotics, clothing and footwear, water supply and miscellaneous services relating to the dwelling, electricity, gas and other fuels, transport services, operation of personal transport equipment, restaurants and hotels, telephone and Telefax services, postal services, recreational and cultural services, newspapers, books and stationery and package holidays.

[14]We scaled the national average consumption expenditure obtained from Eurostat with the share of the household consumption to the national average that is observed in the HFCS according to the formula below: $cons_{hh,eurost} = \overline{cons_{hh,eurost}} * \frac{cons_{hh,HFCS}}{\overline{cons_{hh,HFCS}}}$

probabilities increase. Tables 15 and 16 show the wealth and income inequality across scenarios. Results remain broadly unchanged, with a slightly higher benefit reported in terms of income inequality in the baseline scenario.

6 Conclusion

This study aimed to assess the welfare costs and benefits of borrower-based macroprudential measures from the perspective of wealth and income inequality. We hypothesized that the exclusion of households with lower wealth from the mortgage market may increase wealth and possibly income inequality, due to the contractionary effect of the resulting loan demand shock. On the other hand, we reasoned that the benefits of these policies may accrue in adverse macroeconomic conditions as more resilient banks would reduce the costs imposed by a financial crisis on low-income households. The improved resilience of banks' balance sheets after imposition of borrower-based measures was expected to affect income inequality via the less severe second round effects implied by the credit crunch, notably lower unemployment.

Our counterfactual simulation for four euro area countries shows that the imposition of LTV and DSTI limits in the baseline scenario leads to an increase in the Gini coefficient on wealth by 0.14 percentage points in Italy to 0.58 percentage points in the Netherlands. A similar pattern is observed in the adverse scenario. The unconditional benefit of borrower-based measures is negative in terms of wealth inequality, ranging from -0.14 percentage points in Italy to 0.58 percentage points in the Netherlands.

Turning to income inequality, a marginal decrease is observed at LTV and DSTI introduction, a consequence of the lower debt burden on households, while no difference is observed in the adverse scenario with and without these measures in place. The expected benefit in terms of income inequality is marginally positive amounting to less than 0.16 percentage points in terms of Gini coefficient of income.

The main take-away from this study is that borrower-based measures have a small negative impact in terms of wealth inequality and a negligible positive impact on income inequality. The benefit in terms of income inequality under adverse macroeconomic conditions may be understated since only mortgages issued in one year were included in our simulation. Since only a small share of outstanding mortgages was affected, the relative impact on bank risk parameters mitigating the credit crunch was correspondingly reduced. Future research could consider positive social externalities of borrower-based measures, for instance their potential to reduce status motives for debt accumulation, breaking the negative loop between house prices and credit growth.

7 Appendix

7.1 Mathematical appendix

7.1.1 Minnesota Prior

The Minnesota prior proposed by Litterman (1980, 1986) is the simplest informative prior to use in a BVAR. It is based on the assumption that the variance-covariance matrix is known ($\bar{\Sigma}$). Thus, the remaining tasks are to define the likelihood $f(\bar{Y}|\bar{B},\tilde{\Sigma})$[15] and the prior distribution for $\bar{B}$.

First, for the likelihood, given that the disturbances of the previously specified model are assumed to be normally distributed, it is relatively easy to formulate it:

$$\begin{aligned} f(\bar{Y}|\bar{B},\tilde{\Sigma}) &= \Pi_{t=1}^{T}(2\pi)^{-\frac{nT}{2}}|\tilde{\Sigma}|^{-\frac{1}{2}}exp[-\frac{1}{2}(\bar{Y}-\bar{X}\bar{B})'\tilde{\Sigma}^{-1}(\bar{Y}-\bar{X}\bar{B})] \\ &\propto exp[-\frac{1}{2}(\bar{Y}-\bar{X}\bar{B})'\tilde{\Sigma}^{-1}(\bar{Y}-\bar{X}\bar{B})] \end{aligned} \tag{7.1}$$

Second, the a priory beliefs used in the identification of the prior distribution of $\bar{B} \sim N(B_0,\Omega_0)$ are the following:

- For the mean (B_0): Most macroeconomic variables follow a random walk. Therefore, each variable's own first lag will converge to 1 and further and cross-variable lags to 0.

- For the variance-covariance matrix (Ω_0):
  1. There is no covariance among variables. Thus, Ω_0 is diagonal.
  2. The further the lag, the more certainty its impact will converge to zero. This translates into smaller variance for far away lags.
  3. This is also true for the coefficients of other variables.
  4. The effect of the constant and exogenous variables is unclear. Therefore, the variance for this variables will be larger.

In essence, this prior tries to replicate the following:

[15] Where $\tilde{\Sigma} = (I_T \otimes \bar{\Sigma})$. $\bar{\Sigma}$ means that the variance-covariance is fixed

$$\bar{Y}_t = \bar{Y}_{t-1} + u_t \tag{7.2}$$

These intuitions translate into the following:

$$B_0 = \begin{cases} 1, & \text{if } i = j \textit{ and } l = 1 \\ 0, & \text{otherwise} \end{cases} \quad \Omega_0 = \begin{cases} \sigma^2_{ii} = (\frac{\lambda_1}{l^{\lambda_3}})^2, & \text{if } i = j \ \forall l \\ \sigma^2_{ij} = \frac{\sigma^2_i}{\sigma^2_j}(\frac{\lambda_1 \lambda_2}{l^{\lambda_3}})^2, & \text{if } i \neq j \ \forall l \\ \sigma_{ci} = \sigma^2_i(\lambda_1 \lambda_4) & \text{if exogenous (i.e. constant)} \end{cases} \tag{7.3}$$

Where the hyperparameter λ_1 controls the tightness of the variance, l represents the lag (as the lag goes further, the variance tightens), λ_2 is a cross-variable specific hyperparameter, λ_3 controls the decay, that is, the speed of convergence to 0 for lags greater than 1 (reflecting the increasingly certainty of negligible effect of further lags) and λ_4 is an exogenous variable specific hyperparameter (set to be substantially large).

Finally, since this prior assumes that the variance-covariance matrix is known ($\bar{\Sigma}$), in the interest of the estimation, this paper uses the OLS estimated variance ($\hat{\Sigma}_{OLS} = \frac{1}{T-k-1}\hat{u}'\hat{u}$, considering only the diagonal).

Once B_0, Ω_0 and $\hat{\Sigma}_{OLS}$ have been determined, applying Bayes's theorem, the posterior distribution can be parameterized as:

$$P(\bar{B}|\bar{Y}) \sim N(\bar{\bar{B}}, \bar{\Omega}) \tag{7.4}$$

Where

$$\bar{\Omega} = [\Omega_0^{-1} + \hat{\Sigma}_{OLS}^{-1} \otimes X'X] \ \bar{\bar{B}} = \bar{\Omega}[\Omega_0^{-1}B_0 + (\hat{\Sigma}_{OLS}^{-1} \otimes X')\bar{Y}]$$

7.2 Tables and charts

Table 5: Summary statistics

Country	Variable	Obs	p25	p50	p75	p90
IE	Household gross income	5,381	23,230	41,472	74,533	118,958
	Total assets	4,979	80,600	200,650	375,300	733,321
	Initial mortgage	1,866	100,000	175,000	260,000	365,000
	Value of residence	3,803	120,000	170,000	250,000	375,000
	Stocks	792	700	4,000	18,000	50,000
	Bonds	270	300	5,000	30,000	63,285
	Initial LTV	1,801	68%	91%	109%	200%
	Initial DSTI	2,731	8%	15%	25%	40%
IT	Household gross income	8,037	15,693	25,696	43,431	66,157
	Total assets	7,424	75,200	187,900	320,652	556,900
	Initial mortgage	649	70,000	100,000	140,000	200,000
	Value of residence	5,875	120,000	180,000	250,000	400,000
	Stocks	342	4,745	10,000	20,000	50,000
	Bonds	1,200	11,840	26,000	50,000	85,000
	Initial LTV	606	57%	82%	100%	166%
	Initial DSTI	1,299	6%	12%	21%	34%
NL	Household gross income	1,280	32,032	49,095	73,545	98,393
	Total assets	1,206	147,493	268,682	404,330	614,335
	Initial mortgage	647	91,000	151,000	226,000	310,000
	Value of residence	909	180,000	235,000	320,000	400,000
	Stocks	130	3,133	8,000	21,152	58,900
	Bonds	64	3,011	15,590	96,156	744,152
	Initial LTV	644	77%	103%	127%	211%
	Initial DSTI	779	7%	13%	23%	39%
PT	Household gross income	6,184	10,658	18,415	32,410	51,800
	Total assets	5,644	86,244	161,986	305,000	600,530
	Initial mortgage	2,218	59,800	90,450	134,900	180,000
	Value of residence	5,053	74,631	118,000	175,000	250,000
	Stocks	451	1,000	3,000	8,000	22,900
	Bonds	60	7,950	20,000	55,000	133,000
	Initial LTV	2,151	67%	92%	100%	135%
	Initial DSTI	2,801	10%	17%	27%	44%

Note: The table reports the summary statistics of the variables of interest by percentile of the distribution Data from the Household Financial Conditions Survey (HFCS).

Table 6: Micro data from the HFCS Survey

Assets	Bond holdings	DA2103
	Stock holdings	DA2105
	Financial assets	DA2100
	Other properties	HB2900
	Net wealth	DN3001
	House current	DA1110
Debt	Mortgage outstanding	HB170x
	Total outstanding debt	DL1000
	Monthly mortgage payment	DL2100
	Year of mortgage issuance	HB130x
	Initial value of mortgage	HB140x
	Initial value of the house	HB0800
	Share house ownership	HB0500
	Initial LTV	sum(HB140X)/(HB0500*HB0800)
	Monthly total debt payments	DL2000
Income & expenses	Annual household gross income	DI2000
	DSTI	DL2000/(DI2000/12)
	Unemployment benefit	PG0510
	Employment income	PG0110
	Social transfers (excl. unempl.)	HG0110
	Pension	PG0310
	Real estate income	HG0310
	Rent	HB2300
	Expenses consumer goods	HI0220
Demographics	Country of residence	SA0100
	Country of Birth	RA0400
	Employment status	PE0100a
	Marital status	PA0100
	Education	PA0200
	Age	RA0300
	Gender	RA0200

Note: The table reports the variables of interest obtained from the Household Finance and Consumption Survey (HFCS).

Table 7: Summary statistics by income percentile

Country	Variable	p25	p50	p75	p90
IE	Value of residence	161,822	162,745	185,305	226,008
	Initial mortgage	151,916	148,222	174,640	209,238
	Initial LTV	137.15%	130.69%	116.09%	113.52%
	Initial DSTI	95.06%	31.82%	22.31%	15.73%
IT	Value of residence	138,415	157,869	207,132	232,452
	Initial mortgage	94,000	93,364	115,066	122,411
	Initial LTV	108.58%	94.37%	191.37%	239.42%
	Initial DSTI	115.95%	28.43%	22.11%	15.84%
NL	Value of residence	218,910	245,259	251,906	266,764
	Initial mortgage	209,906	135,089	165,998	208,950
	Initial LTV	207.84%	120.84%	120.62%	123.86%
	Initial DSTI	59.29%	22.69%	21.10%	15.61%
PT	Value of residence	100,987	118,802	139,460	168,584
	Initial mortgage	70,328	82,260	96,606	120,051
	Initial LTV	124.53%	100.08%	114.53%	122.04%
	Initial DSTI	64.78%	31.08%	20.49%	15.87%

Note: the table reports the value of the household main residence, the outstanding mortgage, initial LTV and DSTI by percentiles of household gross income.

Table 8: Employment status

Empoyment Status	IE	IT	NL	PT
Employed	49.37	42.48	51.98	44.55
Sick Leave	1.13	-	0	0.31
Unemployed	13.33	10.71	4.24	13.21
Student	9.83	7.93	10.06	8.34
Retiree	13.98	20.99	16.06	24.79
Disabled	2.26	1.96	4.18	2.17
Domestic tasks	9.11	11.36	8.76	6
Other	1.00	4.56	4.72	0.63

Note: This table reports the proportion of active population per employment status as reported in the HFCS data.

Table 9: Sign restrictions used in BVAR

	CPI	URX	LOANS	INT	WAGE	STOCKS
GDP	+	0	+			
CPI	-		0			
URX		-	-			
LOANS			+			
INT			-			
LTN						
STN			+			
RPP			+			
WAGE		-	+		+	
STOCK			+			+

Note: This table reports the sign restrictions used to identify the credit demand shock in the BVAR. Where "+" indicates the variable is restricted to have a positive effect and "-" negative effect. The credit supply shock is identified analogously, assuming that loan volumes and interest rates move in the same direction.

Table 10: EBA 2018 macroeconomic scenario

Country/Scenario	Baseline rate (%)			Adverse rate (%)		
Unemployment						
	2019	2020	2021	2019	2020	2021
Ireland	5.04	4.88	4.57	6.17	8.59	10.12
Italy	10.31	10.15	9.86	10.65	11.55	12.20
Netherlands	3.60	3.62	3.58	3.92	5.93	8.16
Portugal	6.19	5.54	5.26	6.84	8.02	9.43
House Prices						
Ireland	8.0	6.4	4.8	-2.2	-3.3	-3.0
Italy	1.4	2.0	2.2	-9.7	-7.0	-0.3
Netherlands	5.5	2.8	2.5	-4.2	-8.6	-5.1
Portugal	4.4	4.4	3.9	-4.2	-5.6	-1.3
Long term nominal yields						
Ireland	1.2	1.5	17	2.0	2.3	2.5
Italy	3.7	4.0	4.2	4.9	5.3	5.4
Netherlands	0.7	0.9	1.1	1.3	1.5	1.7
Portugal	2.3	2.7	3.0	3.6	4.1	4.3
Stock Prices						
Ireland	-29.72	-27.10	-21.41			
Italy	-34.58	-31.51	-24.86			
Netherlands	- 29.62	-27.01	-21.34			
Portugal	-29.02	-26.46	-20.91			

Note: This table reports the macroeconomic scenario used in the 2018 euro area stress test run by the ECB and the EBA.

Table 11: Wealth distribution in the baseline scenario

Country	Variable	p25	p50	p75	p90
IE	Net wealth	17,600	119,000	285,000	648,000
	Δ Net wealth	-0.57%	-6.77%	-3.62%	-3.25%
IT	Net wealth	32,517	153,000	291,000	515,167
	Δ Net wealth	-1.09%	-2.76%	-1.94%	-2.47%
NL	Net wealth	29,832	118,990	252,729	415,770
	Δ Net wealth	-6.60%	-6.90%	-2.47%	-2.41%
PT	Net wealth	25,101	78,058	175,400	392,695
	Δ Net wealth	-12.35%	-7.27%	-6.06%	-4.44%

Note: The table shows the percentiles of the wealth distribution in the baseline scenario as well as the percentage change after the imposition of an LTV limit of 0.8 and a DSTI limit of 0.3.

Table 12: Income distribution in the baseline scenario

Country	Variable	p25	p50	p75	p90
IE	Income	37,689	61,166	94,869	134,175
	Δ Income	-0.18%	-0.28%	-0.67%	-0.45%
IT	Income	18,578	31,424	52,467	80,516
	Δ Income	-0.03%	-0.41%	-0.16%	-0.10%
NL	Income	30,581	49,929	76,287	104,500
	Δ Income	-0.12%	-0.53%	-0.08%	0.00%
PT	Income	11,042	19,444	32,368	50,427
	Δ Income	-0.11%	-0.33%	-0.09%	-0.26%

Note: The table shows the percentiles of the income distribution in the baseline scenario as well as the percentage change after the imposition of an LTV limit of 0.8 and a DSTI limit of 0.3.

Table 13: Robustness check 1: Wealth inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline MP=no	Baseline MP=yes	Cost (2)-(1)	Adverse MP=no	Adverse MP=yes	Benefit (4)-(5)	Net benefit (uncond.)
IE	67.14%	67.45%	0.30%	67.14%	67.38%	-0.24%	-0.30%
IT	58.74%	58.80%	0.06%	58.74%	58.78%	-0.03%	-0.06%
NL	56.54%	57.06%	0.52%	56.56%	57.00%	-0.43%	-0.52%
PT	65.28%	65.66%	0.38%	65.46%	65.83%	-0.36%	-0.38%

Note: The table reports the Gini coefficient of wealth across the 4 combinations of macroeconomic and macroprudential policy scenarios. The response of macroeconomic variables to the demand and supply shocks are estimated via linear projections as described in section 5.5. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

Table 14: Robustness check 1: Income inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline MP=no	Baseline MP=yes	Cost (2)-(1))	Adverse MP=no	Adverse MP=yes	Benefit (4)-(5)	Net benefit (uncond.)
IE	37.16%	37.12%	-0.04%	37.38%	37.38%	0.00%	0.04%
IT	40.58%	40.60%	0.02%	40.60%	40.60%	0.00%	-0.02%
NL	34.01%	34.02%	0.01%	34.07%	34.07%	0.00%	-0.01%
PT	42.32%	42.27%	-0.04%	42.47%	42.26%	0.21%	0.05%

Note: The table reports the Gini coefficient of income across the 4 combinations of macroeconomic and macroprudential policy scenarios. The response of macroeconomic variables to the demand and supply shocks are estimated via linear projections as described in section 5.5. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

Table 15: Robustness check 2: Wealth inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline MP=no	Baseline MP=yes	Cost (2)-(1)	Adverse MP=no	Adverse MP=yes	Benefit (4)-(5)	Net benefit (uncond.)
IE	67.14%	67.69%	0.54%	67.17%	67.41%	-0.24%	-0.54%
IT	58.74%	58.88%	0.14%	58.80%	58.82%	-0.03%	-0.14%
NL	56.54%	57.12%	0.58%	56.59%	57.02%	-0.43%	-0.58%
PT	65.28%	65.68%	0.40%	65.45%	65.54%	-0.09%	-0.40%

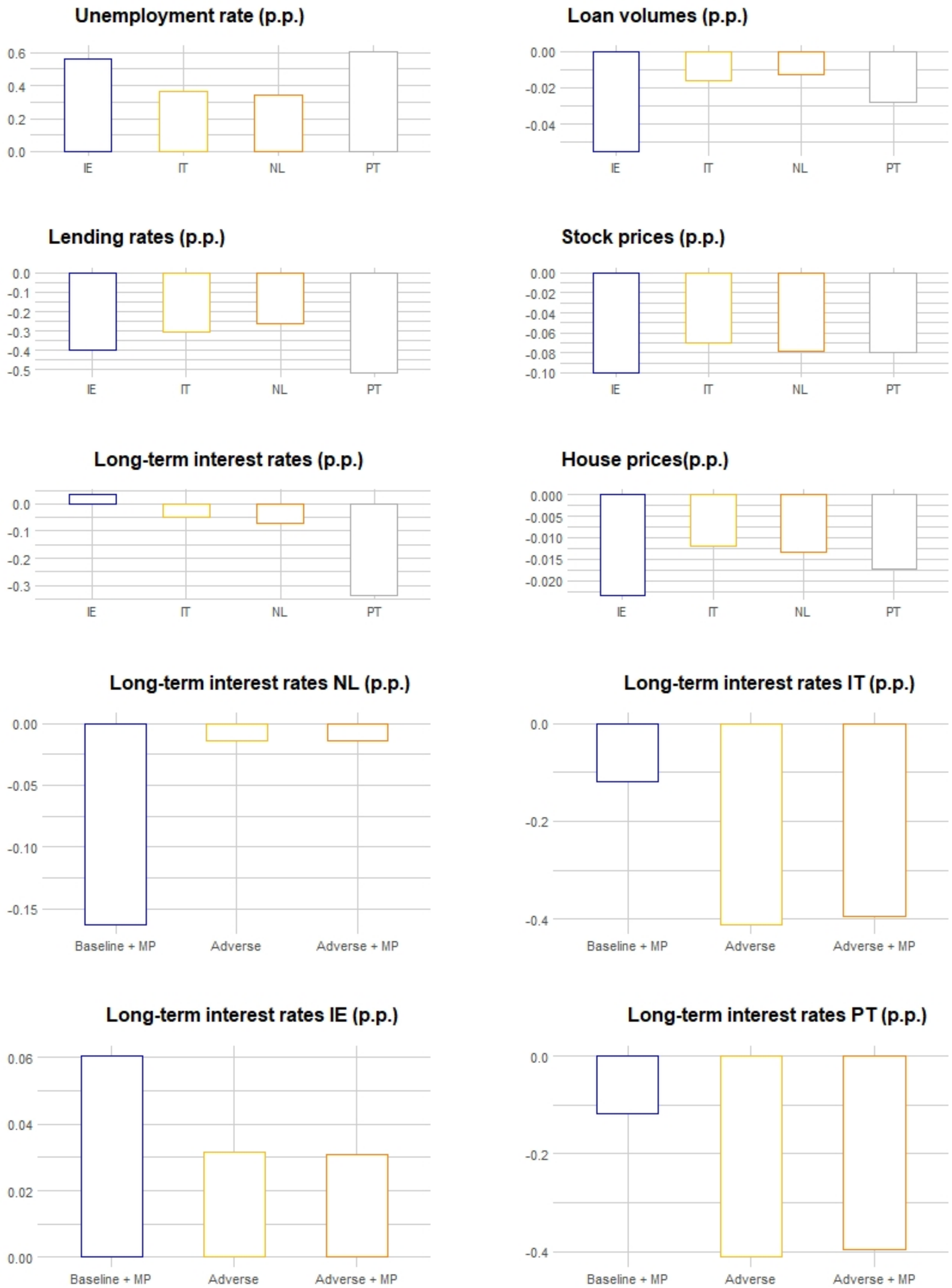
Note: The table reports the Gini coefficient of wealth across the 4 combinations of macroeconomic and macroprudential policy scenarios. Consumption expenditures are rescaled to match aggregate consumption expenditure derived from Eurostat. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

Table 16: Robustness check 2: Income inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scenario	Baseline MP=no	Baseline MP=yes	Cost (2)-(1)	Adverse MP=no	Adverse MP=yes	Benefit (4)-(5)	Net benefit (uncond.)
IE	37.16%	36.99%	-0.16%	37.33%	37.33%	0.00%	0.16%
IT	40.58%	40.54%	-0.04%	40.56%	40.56%	0.00%	0.04%
NL	34.01%	33.97%	-0.04%	34.01%	34.01%	0.00%	0.04%
PT	42.32%	42.20%	-0.12%	42.28%	42.28%	0.00%	0.12%

Note: The table reports the Gini coefficient of income across the 4 combinations of macroeconomic and macroprudential policy scenarios. Consumption expenditures are rescaled to match aggregate consumption expenditure derived from Eurostat. The unconditional benefit in the adverse scenario represents an expected value and is computed as in equation 4.15.

Figure 9. Impulse responses, loan demand shock

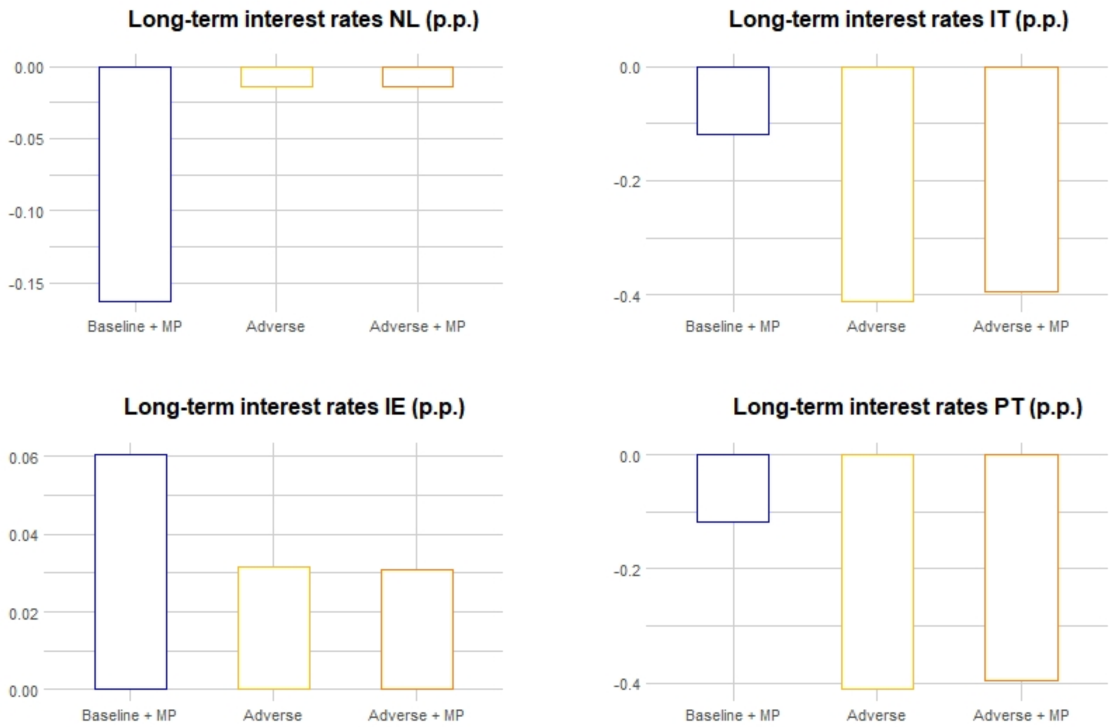


Note: The chart shows the report the cumulative impulse responses conditional on a one standard deviation loan demand shock.

Figure 10. Impulse responses, loan supply shock

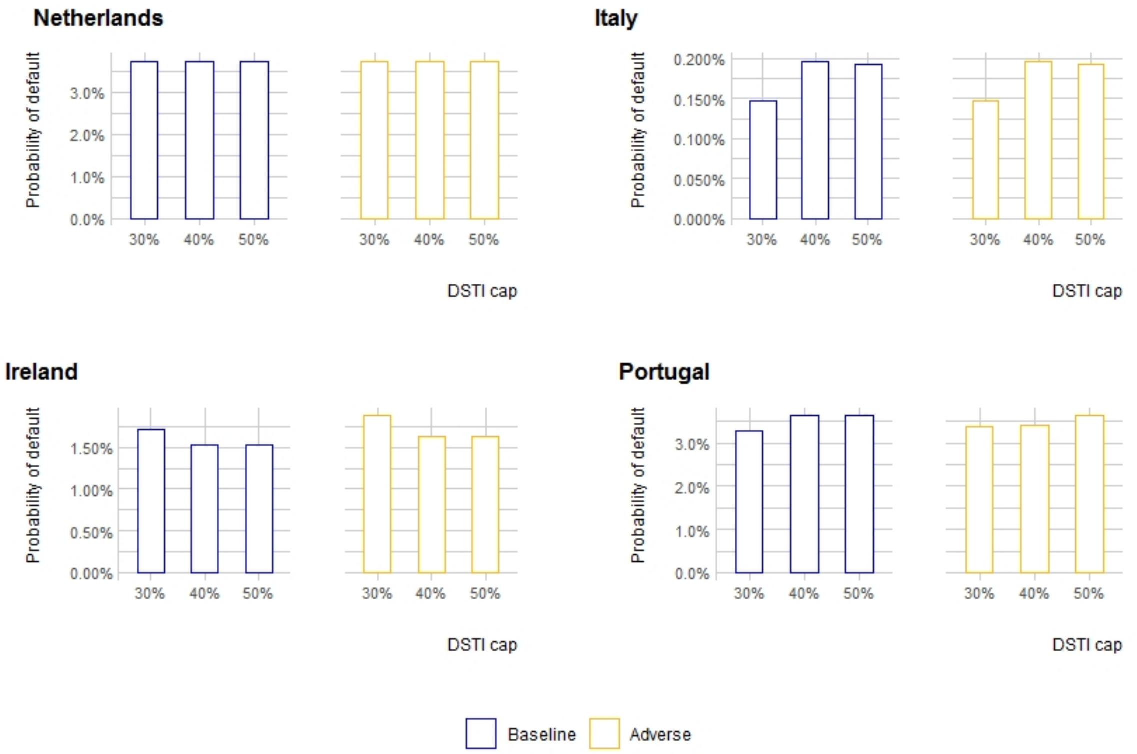
Note: The chart shows the report the cumulative impulse responses conditional on a one standard deviation loan supply shock.

Figure 11. Impulse Responses. Long-term interest rates



Note: The chart shows the scaled impulse responses of unemployment for the different scenarios. The impulse response calculation from the BVAR is described in section 4.1.

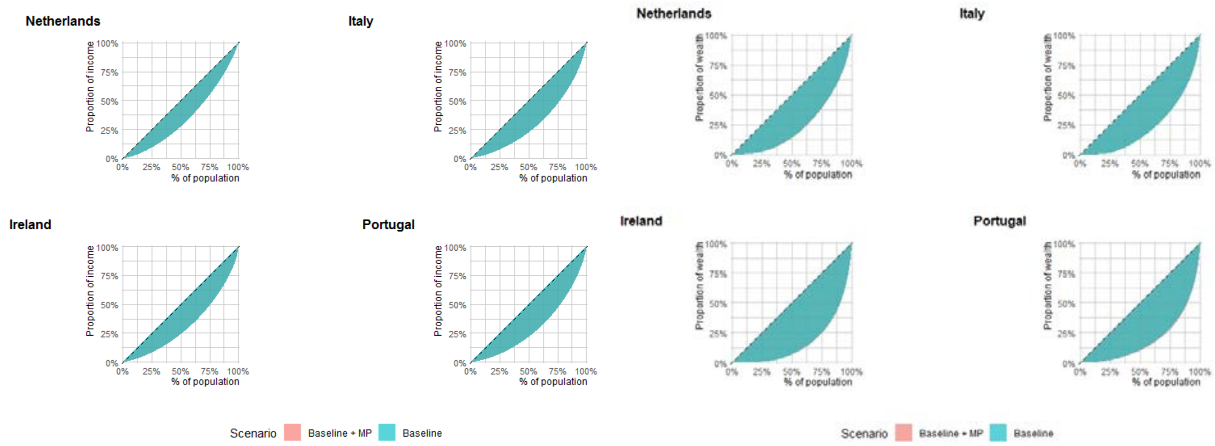
Figure 12. Impact of DSTI limits on PD



Note: The plots the PD after the imposition of different DSTI and LTV limits. A constant LTV of 80% is assumed in addition to the DSTI limits shown in the chart. The charts illustrates the lover volatility of the PD with respect to the different DSTI caps. The PD is obtained from the liquidity simulation in section 4.3.

Figure 13. Wealth and income inequality.

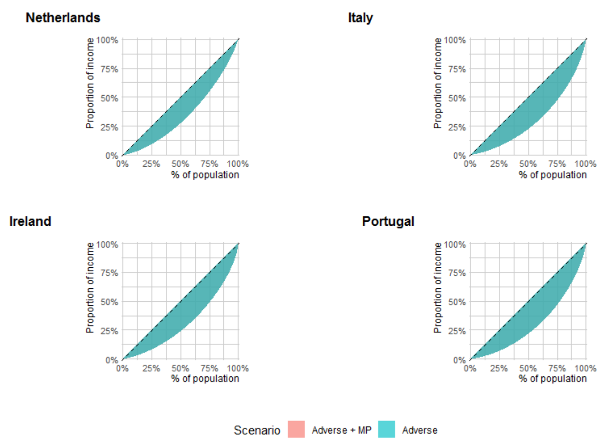
(a) Income (b) Wealth



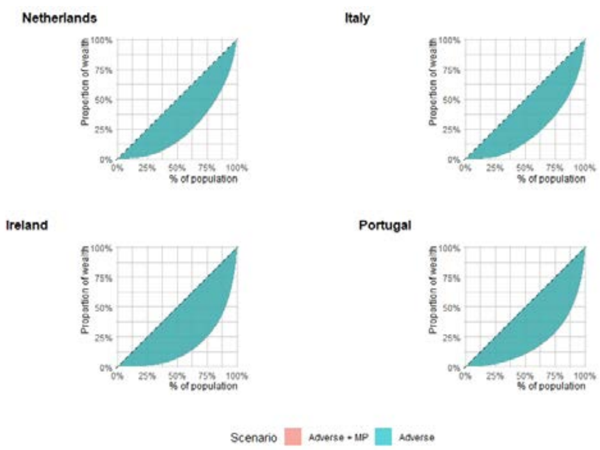
Note: This charts shows the income and wealth distribution by means of Lorenz curves for the considered countries at introduction (baseline scenario). Panel (a) plots the proportion of the total income of the population (y axis) that is cumulatively earned by the bottom x% of the population (x axis). Panel (b) plots the proportion of the net wealth of the population (y axis) that is cumulatively earned by the bottom x% of the population (x axis). In both cases the 45-degree lines corresponds to perfect equality. We observe that income inequality is robust to MP measures (LTV = 80% and DSTI = 30%), whereas wealth inequality shows a slight increase when MP measures are introduced.

Figure 14. Wealth and income inequality. Adverse

(a) Income

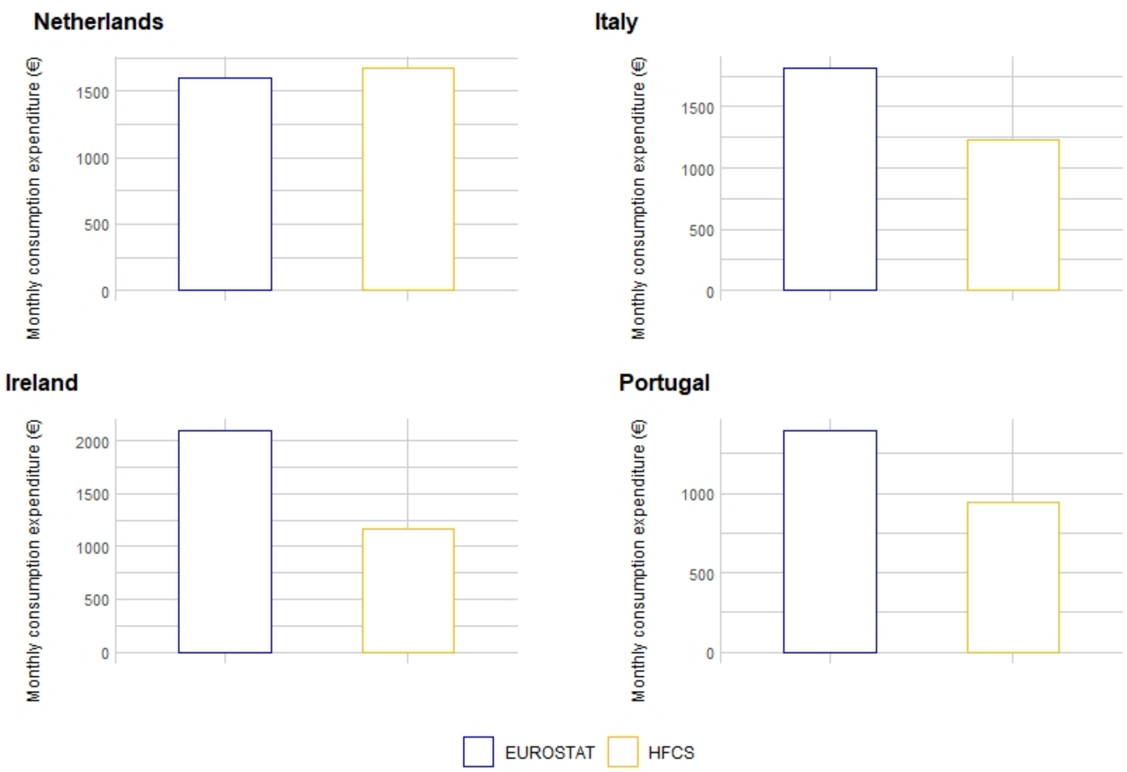


(b) Wealth



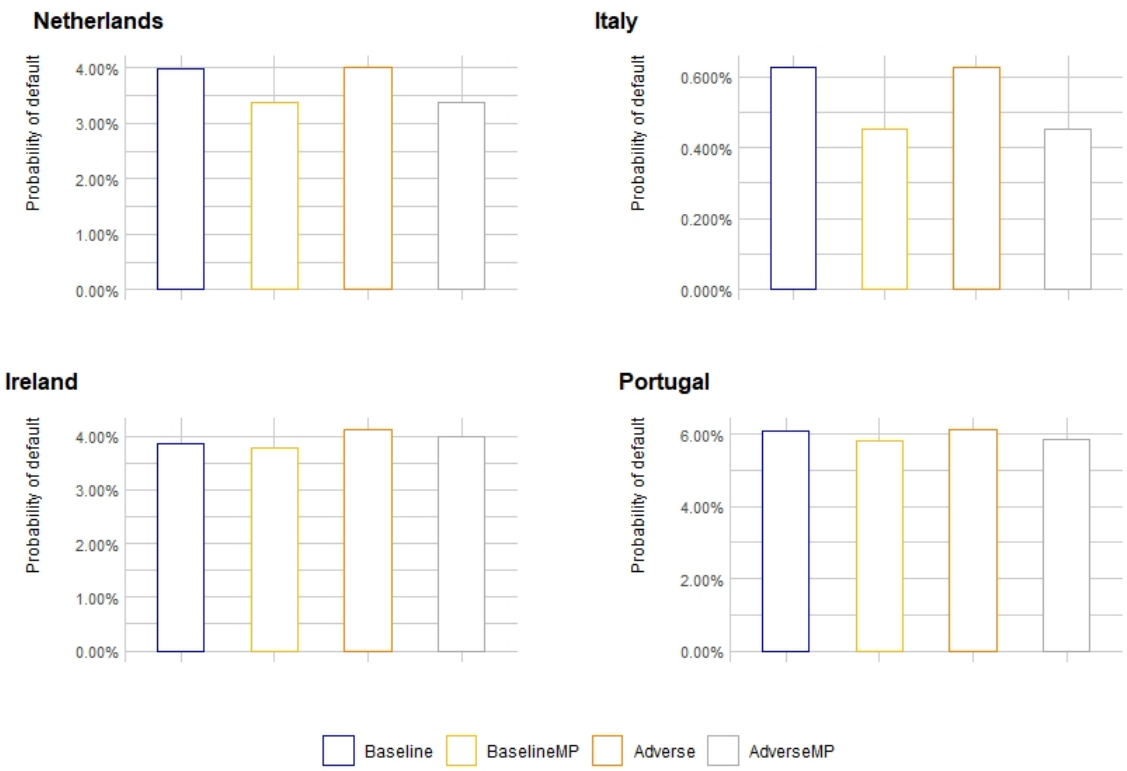
Note: This charts shows the income and wealth distribution by means of Lorenz curves for the considered countries in the adverse scenario. Panel (a) plots the proportion of the total income of the population (y axis) that is cumulatively earned by the bottom x% of the population (x axis). Panel (b) plots the proportion of the net wealth of the population (y axis) that is cumulatively earned by the bottom x% of the population (x axis). In both cases the 45-degree lines corresponds to perfect equality. We observe that income inequality is robust to MP measures (LTV = 80% and DSTI = 30%), whereas wealth inequality shows a slight increase when MP measures are introduced.

Figure 15. Monthly consumption expenditure (EUROSTAT vs HFCS)



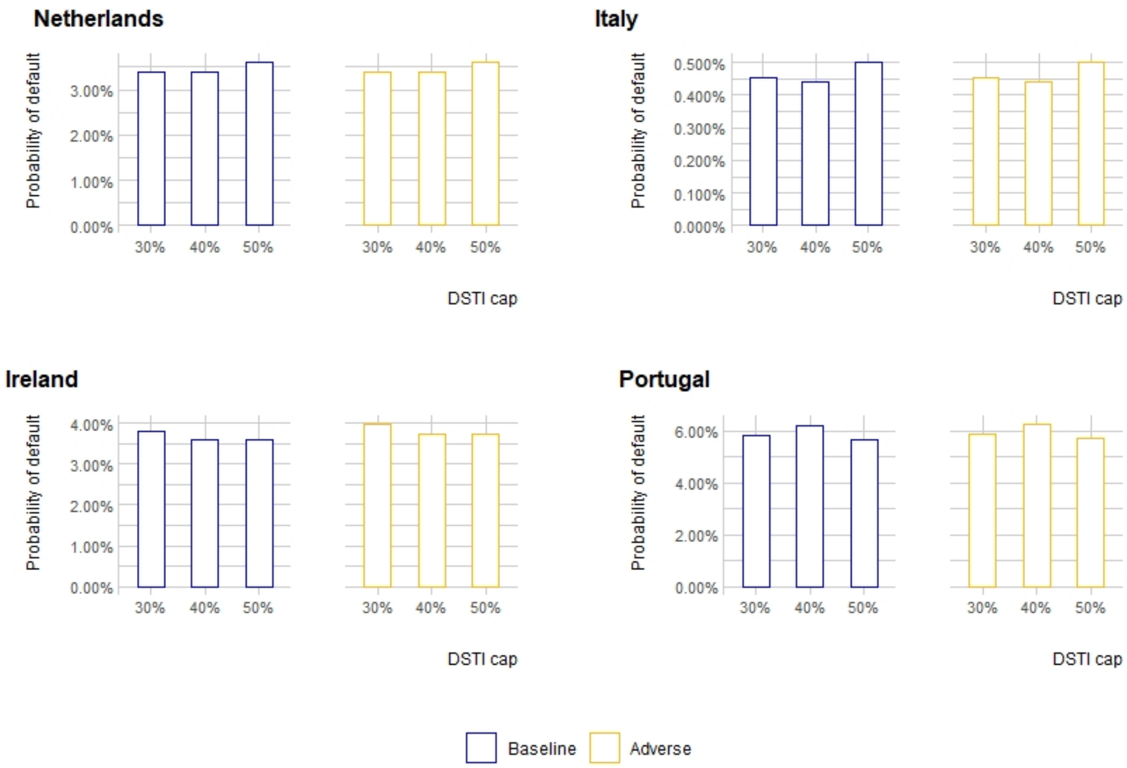
Note: This plots reports consumption expenditures values from EUROSTAT and HFCS. We match the HFCS consumption definition by selecting the most relevant consumption categories from EUROSTAT's Annual National Accounts. The plots show that EUROSTAT's numbers capture the countries' consumption patterns observed in the HFCS while overcoming the underestimation problem from the survey one-shot question design.

Figure 16. Robustness check 2. Impact of LTVs limits on PD



Note: The chart shows the PD before and after the imposition of a DSTI limit of 30% and LTV limit of80% under both macroeconomic scenarios. The PD is obtained from the liquidity simulation in section 4.3 with consumption values from EURSOTAT.

Figure 17. Robustness check 2. Impact of DSTI limits on PD



Note: The plots the PD after the imposition of different DSTI and LTV limits. A constant LTV of 80% is assumed in addition to the DSTI limits shown in the chart. The charts illustrates the lover volatility of the PD with respect to the different DSTI caps. The PD is obtained from the liquidity simulation in section 4.3 with consumption values derived from EURSTAT.

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